Are expert judgments a reliable tool for predicting farmer and food consumer decisions?

Experimental evidence from a forecasting survey

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Abstract

Often trusted to provide sound recommendations and advice, experts from academia and industry are often relied upon throughout industries around the globe, and the food and agriculture industry is no different. We therefore ask, how accurate are these experts, and are they able to accurately forecast behavior from varying food chain actors such as farmers and consumers? Do these experts have a preconceived bias to one side or the other? These questions become increasingly important when considering policy developments such as the EU Farm to Fork strategy, which seek to integrate the consumer-facing food industry and the producer-forward agriculture industry, two policy realms that have historically remained relatively independent of one another. Utilizing a novel hands-on prediction-based approach to collect global results from food, agriculture, and economics experts and non-experts, we analyzed over 2,300 predictions from 87 respondents to determine the accuracy of expert predictions against actual values and behavior, individually and on average. Results are compared against similar predictions from bachelor's and master's students currently enrolled in agriculture-based programs at a Swedish university. We document three primary results; firstly, industry experts do not appear to be more knowledgeable of either given side of the agricultural system, secondly, there is an inverse relationship between higher education and forecast accuracy, and lastly, those with higher self-reported confidence levels showcased incrementally lower predictive accuracy across treatments. We further explore what these findings imply for the future role of experts in the food system.

Keywords: Experimental economics, forecasting, prediction experiment, food-chain actors, food choice, agricultural policy

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Abbreviations

CAP	Common Agricultural Policy
DCE	Discrete Choice Experiment
EPI	Environmental Policy Integration
EU	European Union
F2F	Farm to Fork
GDP	Gross Domestic Product
GM	Genetically Modified
GMO	Genetically Modified Organism
ID	Identification
PDF	Portable Document Format
SLU	Swedish University of Agricultural Sciences
WTP	Willingness to Pay

1. Introduction

The objective of this thesis is to investigate how well experts can predict farmers' and consumers' behavior as compared to real-world results. When we are sick, we consult a doctor, when our car breaks down, we visit a mechanic, and when we have a financial challenge, we visit a consultant. While each employ vastly different fields of expertise, these experts share a mutual commonality: they are relied upon to give helpful and sound counsel based on their advanced expertise, knowledge, and professional background. In all aspects of our lives, we often seek out "experts" within particular fields for their advice and recommendations. Those receiving the guidance generally depend fully on the expert's judgmental accuracy (Dawes et al., 1989), and we frequently believe predictions from experts to be more accurate than those from ourselves. Generally, advice received from experts is trusted and acted upon with minimal secondary thought. The belief is that experts are more knowledgeable, and therefore make better predictions and judgments within their area of expertise (Grossman et al., 2023).

Expert knowledge and their subsequent relationship with lay persons become especially important within the food and agriculture industry. Here, possible challenges from expanding knowledge gaps between consumers and experts are potentially threatening agricultural innovations and the ability to provide a safe, nutritious food supply (Sutherland et al., 2020). Expert knowledge is therefore vital to predict future events and analyze topics such as food security and supply, environmental impacts of legislation, or commodity market alterations from weather. In recent history, food, and agriculture experts from academia and industry have served as a form of liaison between agricultural producers and food consumers on these topics. However, new initiatives within many wealthy, post-industrial societies are seeking to shift the dynamic to create increased farmer-to-consumer interactions with greater access to one another, thereby limiting direct expert engagement. Policy paradigm shifts such as the European Farm-to-Fork strategy, for example, seek to integrate agricultural policy and food policy to newfound levels (Wesseler, 2022). This assimilation between "sides" of the agricultural sectors begs the questions of how clearly agricultural producers understand food policy issues, and if consumers similarly recognize farmers' challenges.

We utilize a novel hands-on prediction analysis experiment to explore and analyze how well food and agriculture industry experts understand both farmers and consumers and if these same experts can better anticipate the actions of one side or the other. More importantly, we question if industry experts are prepared for a shift towards food and agricultural policy integration, or if they are more knowledgeable and potentially biased to either side. Naturally, our overarching research aim led to follow-up questions and additional aims within our research: Do education levels impact the accuracy of forecasts? Does expertise type play a role in predictions? Do experts outperform non-experts? To explore these questions, we utilize existing data from two recent Discrete Choice Experiments (DCEs), expert forecasts, and agriculture-based student forecasts to investigate and collate the extent to which expert judgments are accurate individually, and on average, in predicting consumer food choices and farmers decisions, compared to real stated values. The studies which our research is based upon, and draws data from, were comprised of over 2,500 subjects across 26 various treatments covering both sides of the food and agriculture industry. Responses for these research initiatives were all gathered fully online from within the same country and the same year (2022).

As part of our design, we surveyed experts stemming from several agriculture and economics fields (experimental, industrial, food and agriculture, etc.), industry leaders, and value-chain actors. Contacts were largely collected and aggregated via personal and professional networks of the research team. Respondents were provided a randomized subset of the initial treatments and asked to provide predictions on how they believed respondents in the original studies would have answered. In addition to industry and academic experts, we also surveyed students who were actively enrolled in a relevant food/agriculture program at the Swedish University of Agricultural Sciences (SLU). To retain the integrity of the study, both sample populations were provided with the same survey and overall structure.

Although this type of study is not a new concept in the broader field of economics, the implementation of comparable prediction analyses within the agriculture industry, especially which cover both sides of the food system, remains novel. Following baseline framework set by previous research, especially that of DellaVigna and Pope (2018), Schaak et al. (2023), and Rommel et al. (2022), this study explores how well experts can anticipate the stated actions of a population, both on average, and individually, to determine the efficacy and reliability of expert information in the context of the food and agriculture industry.

The remainder of this thesis will be structured as follows: we will review existing literature on the changing agricultural landscape, reliability of expert judgments, and the potential benefits and outcomes of prediction-based experiments. This will be immediately followed by a further detailed outline of the previous studies with which our expert predictions were baselined against. Next, we will discuss our experimental design and the structure of our survey. After reviewing collected data and discovered results, we will discuss impactful variables and any limitations which may be found within the study.

2. Related Literature

Agriculture is a global and diverse industry full of contradictions, making it unlike many others. In some parts of the world, more than 60% of the population is directly employed by agriculture (Meijerink & Roza, 2007), yet the industry in its entirety accounted for only a meager 4.3% of global GDP in 2021 (World Bank, 2021). Employing much of the global population in economically developing nations, generating food for the ever-increasing world population, and utilizing more than 40% of the world's available land mass (Alston & Pardey, 2014), it remains among the most vital industries worldwide. Contrary to developing nations, who are often heavily reliant on traditional agriculture and related industries for the advancement of their societies, many wealthy Western countries are seeking to shift and integrate the industry to further global sustainability aims, often leading to challenges that have not yet been seen before. Subsequently, this has led to significant societal debates on the correct course of action, often pitting "sides" against one another. Reviewing global headlines surrounding agriculture for the past five years, we see many examples of newly implemented integrated agriculture policies leading to hotly debated challenges or expanding fractures between farmers, policymakers, and the public. Large food and agriculture debates may be seen in climate mitigation policy, gaps within the Common Agricultural Policy (CAP), animal welfare challenges, and even human dietary consumption.

Take the Dutch nitrogen crisis as a key example, where a series of extensive debates and protests were sparked as a result of governmental rulings and newly implemented policies sought to limit the pollution of nitrogen outputs. Although other industries have been impacted by these rulings and policy measures, Dutch agriculture is responsible for nearly half of the nitrogen output in the Netherlands, and these policies have led to considerable negative impacts on vast swaths of producers across the country (Stokstad, 2019). To curb on-farm pollution, the Dutch government implemented measures to limit growth of "peak polluters", and by offering voluntary buy-offs for the farmer's operations. Similar measures have taken place within Belgium; however, the government has begun forced farm buyouts, a move the Dutch government was likely planning to implement (van der Knaap et al., 2022). Dutch farmers have retaliated and protested these measures extensively, bringing the conversation to the world stage. Not only have these actions gathered worldwide attention, but they have also put significant strain on investment and economic growth within the country (Oxford Analytica, 2023). This debate has become highly politicized, and early polling data suggests the Dutch government is likely facing a premature collapse as a direct result of the emission-cut legislation (Oxford Analytica, 2023). Other European countries, likely previously considering similar legislation, have been forced to consider alternatives and consult available experts, or risk severe societal backlash.

We may also find significant debates surrounding the CAP, one of the world's largest agricultural policies, and the longest-standing in Europe. Originally, this initiative was focused on supporting farm production and income but has evolved to emphasize food and environmental policy. This perfectly showcases the trend of wealthy Western countries to integrate food and agricultural policy (Pe'er et al., 2019). Extensive discussion has surrounded the CAP and its viability for success, and if it can address key agriculture and sustainability issues. While the path to success is clouded, there is consensus among Europeans that the CAP does not do enough to address environmental degradation, with 92% of non-farmers, and 64% of farmers believing more could be done (Pe'er et al., 2019). Other debates may be seen in many areas of agriculture and food, such as food growth procedures and the proper human diet. We may point to the long-lasting societal discussions surrounding the utilization of various food growth mechanisms such as all-natural, non-GMO (genetically modified organism), or even the contentious Eat Lancet Commission's reference for the proper diet given environmental impacts (Willett et al., 2019). With these thoughts in mind, we may further necessitate the need for industry experts to help solidify a viable path forward to succeed in program success.

2.1 Agriculture, Food, and Trust; A changing landscape

Due to its importance and overall critical nature, research within the agriculture industry is dynamic and continuously evolving, growing, and changing. Today, where topics such as environmental sustainability, animal welfare, and food safety are of increasing importance to the general population, we see new studies and publications being released frequently across the agriculture industry.

With the rise of modern technological advancements, the world has and will continue to change drastically. Although often slower with the uptake of new technologies, the agriculture industry is no different. Today in post-industrial societies, it is not uncommon to see agricultural producers with state-of-the-art machinery and equipment to manage crops or monitor livestock health. Contrary to previous times, many producers now have access to a virtually limitless stream of information, all from the palm of their hand. Historically, though, farmers have relied on in-person advice from experts regarding farm management practices (Rust et al., 2022), especially those that involve any direct changes in process. These in-person discussions were vital for agricultural producers as any change in farm operations carries a high risk and could directly impact their livelihood. As such, many farmers tended not to trust information coming from individuals or groups with no farming experience (Mauro et al., 2009, Skaalsveen et al., 2020). This technological shift shows a potentially significant movement in the agricultural landscape as farmers begin to increasingly receive, utilize, and/or trust information coming from sources other than direct conversations with experts. In a comparative study comprised of 82 farmers in the UK and Hungary, research conducted by Rust et al. (2022), found that "modern" farmers place the most trust in other farmers, especially when being asked to alter current operations. These farmers were less trusting of experts, especially researchers from academic or governmental organizations, whom they deemed were no longer sympathetic towards their needs. This research went on to surmise that farmers may have had enough of "traditional experts" and choose to increasingly rely on their peers and personal networks to learn and innovate their operations (Rust et al., 2002). Given this information, unsurprisingly, some producers are shown to have greater trust in producer-owned companies (cooperatives), than they do in firms owned by the general public (James & Sykuta, 2006).

Trust can be a challenging construct, though, and largely depends on the subject which is being discussed and the parties involved. Contrasting farmers' views, experts, especially those from Academia, are found to have widespread public trust based on a study conducted within the UK (Wellcome Trust, 2019). However, when discussing food-related topics, such as GM (genetically modified) food products, respondents often have a generalized lack of trust in experts from any faucet, whether it be from academia, governmental institutions, or industry. In this mentioned study, public trust levels (or the lack thereof) remained interchangeable between all groups (Shaw, 2002). Interestingly, when comparing consumer trust levels within agricultural food system actors, it was determined that consumers have the least trust in farmers and industry leaders (Lang & Hallman, 2005). This level of trust is imperative, because at its most fundamental level trust is equated with cooperation (James, 2002).

In our context, trust levels between agriculture experts, consumers, and producers are of increasing importance due to contemporary shifts in the agriculture industry which emphasize expanded direct connection between farmers and end-consumers. We may see these connections at a food transaction-based level, through the expanded use of regional markets offering locally produced and sourced goods directly from farmer to consumer. We may also see this at a policy level, looking towards programs such as the EU Farm to Fork strategy (F2F), as one example. At the heart of the European Green Deal, the F2F program is comprised of topics on food, health, and the environment, which seeks to transition to a more sustainable food system through the reformation of existing agricultural and environmental policies (European Commission, 2020). The concept of policy integration is not new within the EU and has predominantly been conceptualized via environmental policy integration (EPI) (Bazzan et al., 2023). Existing research, however, has shown the EU has struggled to implement and attain EPI in practice (Alons, 2017; Jordan & Lenschow, 2010; Persson et al., 2018). This disappointing track record for European policy integration success surmises the F2F program will be challenging to implement and likely will require innovative solutions (Bazzan et al., 2023; Howlett, 2017) to succeed. Research continues to expand on the viability and challenges which may be faced for this program, and others like it. Academics, including Wesseler (2022), have showcased that F2F will likely have negative effects on aggregate consumer surplus, and depending on the assumptions made, an increase or decrease in producer surplus, thereby leading to an overall net welfare loss. Further, traditionally, agriculture policy and food strategies are formed mostly in isolation from one another (Petetin, 2020), with experts often working as a form of intermediary between farmers and consumers. The economic limitations of integrations, however, will likely draw upon and require experts' knowledge of both sides of the agricultural system to succeed. Regardless of success, unequivocally, this sets the stage for increasing not only policy overlap between the agriculture and consumer/food industries in Europe, but also for the rest of the world.

In some respects, we may compare some F2F goals, especially the concept of policy amalgamation between consumer food-based programs and agricultural schemes, to that of the Energy-Food-Water Nexus approach which is often discussed in sustainability-related projects (Smajgl et al., 2016). At its baseline, this scheme considers the relationships and interactions among these resources as well as any possible synergies or trade-offs which may exist (Alrebei et al., 2023). While this concept is largely related to the specific interactions between water usage, food growth, and energy, it places strong emphasis on the connections occurring. We may draw similar parallels of importance to the connections between experts, consumers, and farmers, which must occur to prepare for adequate policy creation, integration, and implementation within the agri-food landscape.

2.2 Forecasting analyses. The new economic norm?

Upon opening any scientific journal, especially those related to agriculture, we see every conceivable form of statistical analysis, modeling, or simulation to understand the complicated dynamics and interdependencies within agriculture. By employing a diverse range of measures, researchers can predict future scenarios, optimize resource allocation, assess risk factors, and devise innovative strategies to enhance productivity, sustainability, and profitability in agriculture. These analytical techniques play a vital role in informing industry stakeholders about the potential outcomes of various interventions, thereby enabling evidence-based decision-making. However, within such journals, we rarely see any form of forecasting measure being utilized or considered as part of the "status quo" for the agriculture industry. This science of analyzing forecasting success, especially with subject matter experts, has largely been concentrated on geo-political (Tetlock, 2017) and economic events (Makridakis, 2020), especially those with single point occurrence (Mandel, 2014). When forecasting does occur in economics, it is generally completed ex-post, after the results of a study are known (DellaVigna et al., 2019). While this is generally in line with scientific process, due to hindsight bias, it can be that the true expectations or forecasts of the expert remain unknown. The analysis of expert predictions can provide a number of key benefits to the research process and improvement to current knowledge and beliefs. Predictions offer a mechanism to elicit ex-ante beliefs on a study, aiding in the limitation of a hindsight bias, as it draws a clear line on "who knows what" (DellaVigna et al., 2019). Further, regular, and systematic predictions can facilitate more accurate future predictions, and influence future research designs (DellaVigna & Pope, 2018; Milkman et al., 2022).

While economics may have a history of studying predictions (Ben-David, et al., 2013; Snowberg et al., 2007), to date, only a small body of literature has sought to extend these works into gathering forecasts from original works or academic studies (DellaVigna et al., 2019). The agriculture industry specifically has largely remained untouched by any form of ex-post prediction-based analyses from DCEs. This limited attention stands in stark contrast to the ever-expanding social-science literature regarding individuals' ability to make general predictions about every-day events (Griffiths & Tenenbaum, 2006), and the increasing attention at reproducing academic research results across many industries ranging from medicine (Begley & Ellis, 2012), political science (DellaVigna et al., 2019), and economics/experimental analysis (Roth, 2018). While there are relatively few studies showcasing prediction accuracy on non-market aspects or studies, we may point to some smaller-scale projects which involve eliciting opinions from experts within certain fields. For example, Sanders et al., (2015) compares the predictions of student and faculty from a UK university on the results from several studies.

2.3 Possibilities at the intersection of trust and forecasting

When reviewing natural gaps in forecasting analysis, rapidly evolving policy dynamics, and shifts in farmer and consumer trust, we arrive at a relatively large exploration opportunity. The agriculture industry in nearly all post-industrial economies is rapidly changing, and the mindsets of those involved are evolving equally. With trust dynamics shifting due to newfound technologies, opportunities for information dissemination and collection, and evolving research, we believe there is opportunity to widely investigate how these three groups involved in agriculture (consumers, farmers, and experts) interact. Specifically, how well experts know and can predict the actions of both sides of the industry in a straightforward setting. These interactions become increasingly important upon the introduction and implementation of far-reaching policies, such as the F2F, which integrate consumer and farmer policy and will likely rely heavily on industry leaders and experts' knowledge of both farmers and consumers to craft new policies. It is at this point that our research and its aims become pertinent within the industry.

Generally, predictions of experimental outcomes within the agriculture industry have been relatively narrow and mostly understudied. As a result, there are very few research cases that illicit the successes of forecasts or predictions within this industry. Seemingly, we may point to only two known works within agriculture economics with which we may compare results and draw inspiration. Our work may be most similar to that of (1) Schaak et al. (2023), which elicits predictions from 561 students, farm advisors, and experts from Italy, Poland, Croatia, Spain, France, Sweden, and the Netherlands on farmers' risk preferences. Further, we may look to research by (2) Rommel et al. (2022), which elicits predictions from 212 experts on the experimental outcomes in a public goods game, stemming from research on German farmers' willingness to engage in contracts to address agri-environmental policy goals.

The aforementioned studies, such as the work by Schaak et al. (2023), or other comparable literature outside of the agriculture industry, emphasize mostly risk-based predictions with generally complicated forecasting analyses. Further, most comparable works are relatively narrow, focusing on one side of the agricultural system, i.e., farmer-producers or end consumers. It is here that we believe our research begins to showcase its novelty and contributions where previous literature has been left unexplored for three primary reasons. (1) We emphasize and collect straightforward predictions from respondents within the food and agriculture industry, which has been largely unexplored with this mechanism of research, (2) we showcase consumers, farmers, and industry experts, covering all sides of the agricultural industry, and (3) we determine if levels or varying expertise have any impact on knowledge or forecast accuracy.

While our research aims to illicit forecasted beliefs from experts, it may be tangentially related to literature by Breznau et al. (2022), which sought to compare results from 73 research teams analyzing the same dataset with the same research aims. In this study, results were widely dispersed, and the subsequent conclusions from experts were additionally divergent. It was concluded that researcher expertise, prior beliefs, or expectations had little to no effect on the outcomes, and 95% of variance remained unexplainable. Within our results, we similarly compare impactful variables for experts and students alike. We may presume that some levels of variability within predictions are inevitable, as even the most well-intentioned scientists or experts may not converge in their findings due to the complex and ambiguous nature of analysis (Breznau et al., 2022). Industry experts are often confronted with a continuous stream of decision points, which while seemingly inconsequential on their own, combine to provide the possibility of large differences in outcomes. Given such, we may therefore justify certain levels of variability within our prediction study, and the prior literature with which we compare against.

3. Research Methodology

3.1 Description of utilized studies

At the backbone of this research lies two previous studies which our respondents (experts and students) are tasked to predict. Showcasing preferences of both consumers and farmers, these datasets retain several similarities which made them of interest to utilize within our research. These studies were similar in that they both asked respondents for preferred alternatives given changing variables, but differed in that one focused on consumer choice in dairy-based food products, and the other emphasized dairy farmer decision-making for cattle feeding regimes. We include both within our analysis, as experts within the agriculture industry are often asked to provide predictions and analysis on the entirety of the value chain.

Firstly, both studies collected their dataset within comparable timeframes, and are recent (2022). Therefore, we may presume that the collected responses and dataset are reflective of decisions made by consumers and farmers in a (relatively) similar market environment. Both studies were also able to collect a significant and largely representative sample of the targeted population, allowing us to make further inferences within our subsequent prediction sets. Additionally, both studies utilized a DCE and focused on elements within the agri-food value chain. Both prior studies stemmed from Swedish-based research and therefore were offered only in the Swedish language to respondents. To obtain a more global response to our research and to target participants/forecasters outside of Sweden, it was necessary to translate the survey contents and responses for both prior DCEs. All necessary information, tasks, currencies, and data underwent a multi-stage translation review process for the inclusion of English and relevant currency values (Euro) prior to being included in our survey for our research.

It is important to note, however, that due to the relatively recent nature of these studies and ongoing publication efforts only pertinent information, data, and results from earlier research will be included within this report. This is done to preserve the integrity of these studies and their subsequent publications.

3.1.1 Consumer study

Comprised of two separate DCEs, this study aimed to investigate consumer preferences for dairy cattle grazing within dairy products. By Swedish law, dairy cattle should have access to outdoor grazing, however, this research aimed to better understand consumer preference for increased levels of grazing, as compared to the described status quo. Two variations of the survey were created, differing in the dairy product being evaluated by the consumer, whether hard cheese or fluid milk. The survey was comprised of four sections, which included an informative overview, respondent screening, the DCE, and demographic information. Utilizing an online platform and hired marketing agency, the survey was distributed to Swedish consumers from October 24 to November 23, 2022. In total, 2,766 responses were gathered for both experiments, with 1,357 responses collected for the milk-based survey, and 1,409 responses collected for the cheese-based survey. To proceed with valid responses only, the research team cleansed the data on three (3) parameters: (1) if the respondent personally consumes milk, (2) if the respondent passed an attention bias check, and (3) if the response was fully completed. Following this cleansing, a total of 2,131 valid responses were obtained for both the milk and cheese surveys (N = 1,068 for milk and N = 1,063 for cheese).

Within each DCE, respondents were presented with ten tasks in a randomized order where they were asked to choose between two product offerings or to opt out from the purchase. The products varied in their attributes: grazing requirement (in hours), origin (Swedish or imported from other EU-country), and price (SEK) per kg. An original sample of each task may be seen below within Figures 1 and 2.

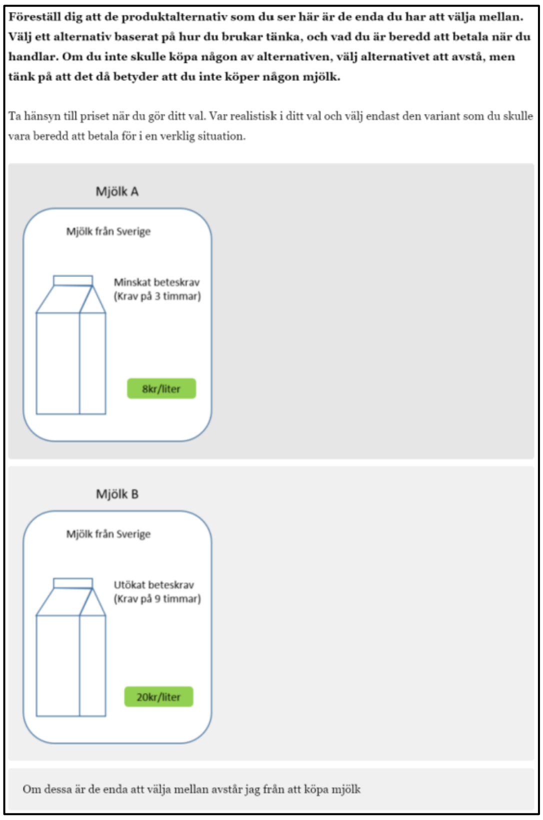

Figure 1: Sample task from consumer cheese DCE

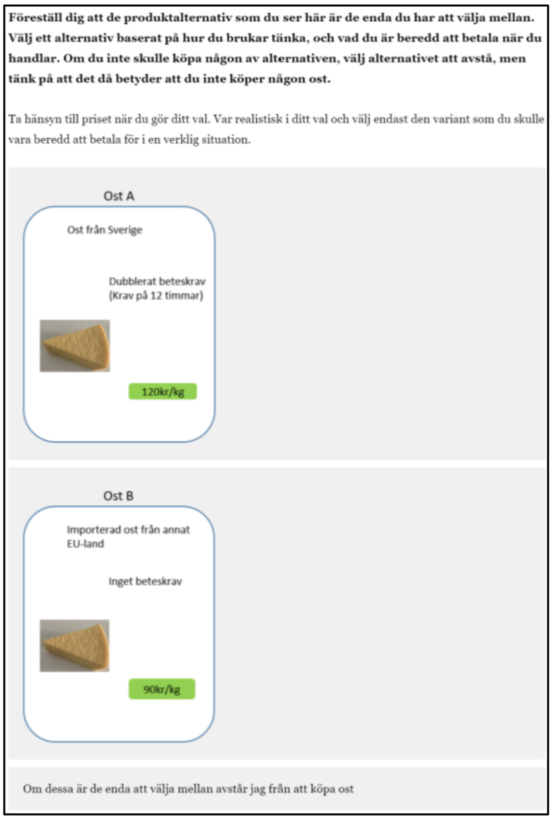

Figure 2: Sample task from consumer milk DCE

3.1.2 Farmer Study

This research aimed to explore environmental, financial, and social trade-offs that farmers may make when choosing between various feeding systems for their dairy cattle. Focusing specifically on state-registered Swedish dairy producers (N = 2,313), this survey was distributed online from August to October of 2022. A total of 375 farmers provided complete and valid responses, resulting in an effective response rate of 18.3%. This method of online-based research is common among Swedish farmers, helping to result in a relatively substantial response rate, as compared to farmers within other geographic locations. However, this research employed the use of a hired marketing agency to gather and anonymize responses. The survey contained three components: farmer and farm characteristics, a DCE, and attitude/identity indicators.

In the DCE, respondents were presented with a sequence of six tasks, each having two proposed hypothetical options of more grass-based feed rations and a status-quo option, as well as an opt-out. The eight hypothetical options are described by different sustainability attributes associated with dairy feeds with attribute levels that vary over the feeding options. Respondents were asked to choose their preferred option for each of the six tasks, acting as if they were making the decision in “real life”. Attributes included greenhouse gas (GHG) emissions, animal welfare, feed cost, biodiversity, feed self-sufficiency, and milk yield, which represent the environmental, social, and economic sustainability impacts of alternative feeding systems. A sample of an original task may be seen in Figure 3.

	Foderstrategi A	**Foderstrategi B**	**Foderstrategi C**
Växthusgasutsläpp	-20% minskning	0% (Oförändrad)	Varken A eller B. Jag skulle behålla mitt nuvarande foderstrategi
Djurvälfärd	Stor förbättring	Ingen förbättring	
Mjölkavkastning	0% (Oförändrad)	-10% minskning	
Biologisk mångfald	Liten förbättring	Stor förbättring	
Självförsörjning av foder	0% (Oförändrad)	+20% ökning	
Kostnad	-20% minskning	-10% minskning	

Jag skulle välja foderstrategi A [ ] foderstrategi B [ ] foderstrategi C [ ]

Figure 3: Sample task from farmer cattle grazing DCE

3.2 Survey Design

The primary objective of our survey was to obtain predictions on how experts and non-experts believe respondents in the previous surveys answered. Further, we hope to investigate other variables which may affect forecast precision. Our survey consisted of five sections and was offered in both English and Swedish, with the ability to toggle between languages at any point. Within the first section, respondents were provided information on the topic, provided their consent to engage in the survey, and given an overview of the upcoming tasks. In sections two, three, and four, respondents received the prediction sets, with one section for each prior survey. These sections were randomized for each respondent to limit any potential anchoring or ordering bias effects. Each of the prediction sections began with a similar introduction which also provided necessary information from the study. While summaries were concise, respondents were provided links which opened PDF (portable document format) files containing more detailed information from the original studies such as graphical illustrations, texts, and all task scenarios in both English and Swedish. It was communicated to respondents that they should not be directly answering the predictions with their preferences, but rather how they believe previous respondents answered, on average. As such, it was also clearly defined that the total value for each prediction must sum to 100%, and respondents would not be able to progress to the next page should this not be completed.

For each prediction task respondents were provided a side-by-side comparison of the alternatives, then they could provide their prediction for responses via a sliding scale from 0% to 100%. Respondents additionally had the option to manually enter values, should they wish to do so. A sample of the task may be seen in Figures 4 and 5, below. Attempting to reduce respondent cognitive strain and limit any potential decision fatigue, each respondent received a randomized subsection of the initial tasks. Following each prediction set, the section concluded with a personal confidence rating on how the respondent believed they answered the provided predictions.

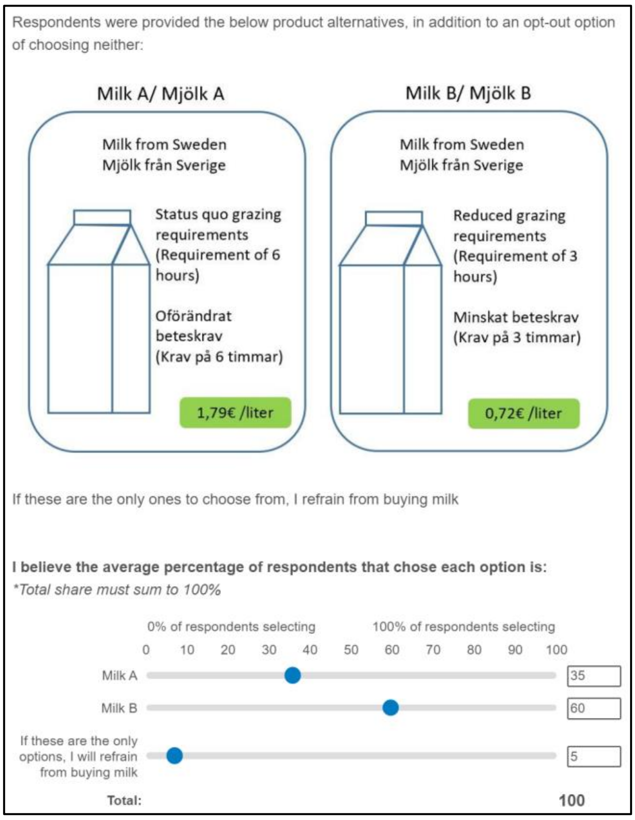

Figure 4: Sample milk prediction task

Figure 5: Sample cheese prediction task

In the fifth and final section, respondents received socio-demographic questions and were asked to assess their self-perceived knowledge of the topic. As the samples consisted of experts and students alike, we asked demographic information (age, gender, residency, etc.), educational background and level, field of expertise, employment status, and knowledge of topics such as agriculture economics, and agri-food policy schemes.

Similar to Rommel et al. (2022), this survey was incentivized, and incentive parameters were clearly stated within the survey introduction. At the end of the survey, respondents were provided with a field to enter their email address and select if they would like to be included in the compensation scheme. For every forty (40) fully complete responses which also provided a valid email address, one response was chosen at random to receive compensation of up to 500 SEK (approximately 44 Euro) based upon their prediction accuracy. One of the nine completed predictions was chosen at random to review for accuracy. If the value of this prediction fell within ±10% of the real value, compensation would be delivered. A total of 190 responses were collected for this survey, from which 87 could be included in the lottery for compensation, due to incomplete responses, lack of email, or selection of the opt-out option.

3.3 Experimental Design and Randomization

In total, the survey consisted of twenty-six scenarios for which forecasts were gathered. As aforementioned, respondents received only a randomized subset of these twenty-six scenarios where they were asked to predict how they believe respondents in the original study answered. This is largely due to the high quantity of scenarios and the time required to complete each forecast. In total, each respondent provided forecasts for nine scenarios: three for consumer milk preference, three for consumer cheese preference, and three for farmer grazing preference. Scenario randomization was established within Qualtrics and was relatively equally distributed among all scenarios.

The survey consisted of multi-level randomization to limit any potential heuristics or anchoring effects which may occur due to the order in which scenarios were received. At the highest level, randomization occurred between which of the two studies respondents were asked to forecast first (consumer or farmer). As such, respondents may have been initially faced with predictions for farmer preference or consumer preference, and this was equally distributed among each of the two. At the next level, randomization occurred within the consumer section, as it was composed of two subsections for consumer preference for fluid milk (1) and cheese products (2). Randomization between these subsections was also evenly distributed among all respondents. Finally, at the most granular level, randomization occurred for the scenarios within each subsection respondents received, as well as the order in which the scenarios were presented. A graphical representation of the survey flow and randomization structure may be seen in Figure 6.

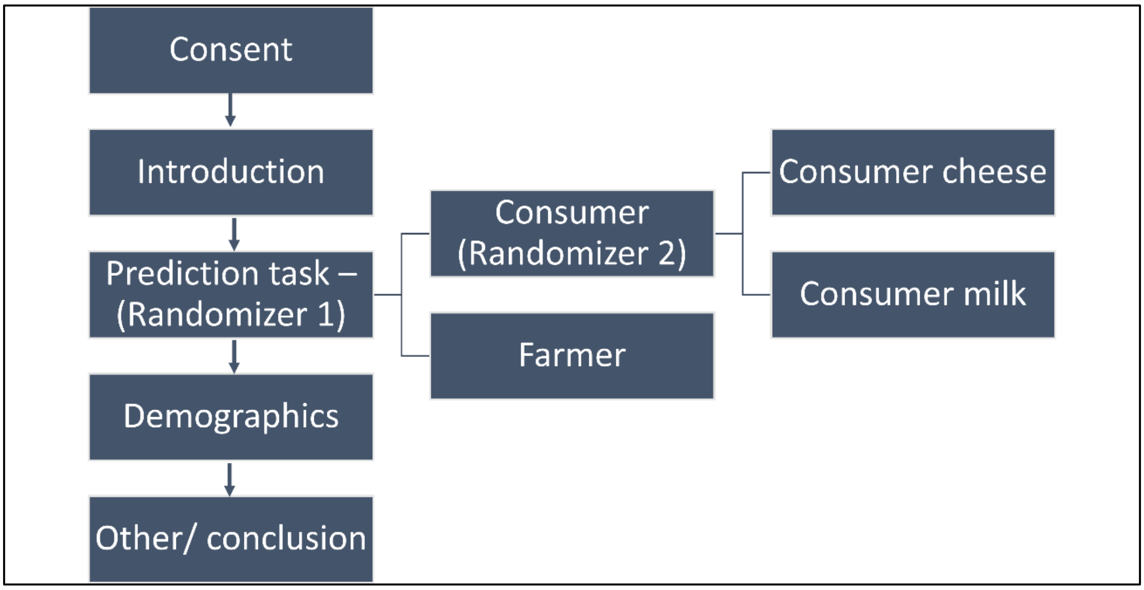

Figure 6: Survey flow including randomization structure

3.4 Data Collection

To examine the accuracy and reliability of expert judgments in the food and agriculture industry, this study collected data from a sample of experts which included (but was not directly limited to) economists, academia professionals, and industry leaders from throughout the agri-food value chain.

Participants were recruited through a combination of professional networks, email distribution lists, and social media. This included the utilization of multiple professional distribution email lists from agriculture economics to reach a large audience of researchers and academic experts. Further, direct emails were sent to peer researchers, previous colleagues, and interested professionals to gather responses. In addition to these, participants were also obtained from a research collaborator, the Mistra Food Futures program, to disseminate the survey among a variety of leaders within the industry. Individuals within this obtained contact list included leaders from both large and small value-chain agriculture operations, food production firms, alternative foods, public policy, technology, and production agriculture fields. However, to reach a larger audience, social media platforms such as LinkedIn and Twitter (rebranded as “X”) were utilized to elicit additional responses. To retain response validity, we ensured links to access the survey were distributed to appropriate and targeted groups.

While this study aims to primarily review the reliability of expert predictions within the agri-food context, an additional sample of responses was collected from students actively enrolled within agriculture-based studies to compare against the aforementioned expert predictions. Students were contacted via email and selected based on their course of study, ensuring it was related to food and agriculture.

4. Data Characteristics

Compiling responses from both experts and students, a total sample of N = 190 was reached. Following the removal of surveys that did not provide approved consent or incomplete submissions, an updated final N = 87 was obtained. This total viable sample size is comprised of 48 experts and 39 non-experts/students. Provided the number of predictions per respondent, this allows for 2,349 observations (27 observations per respondent) which we may utilize within our analysis. Further details on these observations may be found within the immediately following section(s).

4.1 Data Cleansing

This survey utilized fully anonymous and private links; therefore, we were unable to capture the number of individuals who viewed the survey or followed the link to the opening page. However, as of the survey closing date, a total of 190 responses were collected, and following data cleansing, we were left with a total of 87 responses. While several survey responses did not provide consent within the primary page (thereby removing them from the collected sample), we may speculate that some of the removed responses occurred via response fraud. If this is indeed the case, it likely occurred in the form of a bot or system-generated answering mechanism. Nearly the entirety of these responses provided initial consent to the survey but were unable to answer any further questions and subsequently left the survey open for an extended duration. Many of these responses opted into the survey within the opening screen but were uninterested to progress further within the survey, unable to navigate the multi-page structure of the survey or to utilize the sliding bars which were employed within our forecasting structure. However, the presence of machine-generated responses remains speculative. It is plausible that many individuals accessing the survey were uninterested given the lengthy instructions, or simply gave up after accessing. Additionally, it is possible that our results contained a mix of respondents dropping out as well as machine-generated responses. Regardless of the reasoning, these incomplete responses were removed leaving with a final viable count of N = 87, or approximately a 46% completion rate.

4.2 Evaluation & Consolidation

Following data cleansing, it remained necessary for us to collate our prediction statistics into a format with which we could compare results to one another, but more importantly to values from the original experiments. While there are a number of mechanisms with which to compare the real and forecasted values, we chose a relatively straightforward path of utilizing the percentage-point deviations between real values previously obtained, and forecasted values collected within our research. To complete this, we first had to return to the datasets from the two previous DCEs, each of which were utilized to provide the proportion of the sample that chose each option within every individual scenario received. For example, within the consumer dairy preference study (referring previously to Figure 1), the percentage of total respondents selecting each option of Ost/Cheese A, Ost/Cheese B, and neither/ opt-out was calculated. This same process was completed for each of the 20 scenarios within consumer dairy preference and the six scenarios within farmer preference for dairy cattle feeding regimes. A summary of the statistics from both DCEs may be found in Appendix Tables 1 – 3. A numerical variable showcasing the real decision value for each option within the 26 scenarios was then added to our dataset. Similarly, a new variable showcasing the predicted value for every option within every scenario was added to our dataset. Upon the creation of these variables, we were able to calculate the percentage-point deviation between them, providing us with a total of 2,349 deviation observations.

As previously mentioned, randomization was structured into our survey design in three ways: which of the two prediction sets were presented first (1), the ordering of the two consumer preference situations (2), and the overall ordering of each of the received scenarios (3). Variables for each of these randomizations were added to be utilized to determine if the forecasting order retained any impact on accuracy.

4.3 Respondent Demographics

In the final block of our survey, demographic questions were asked of respondents. Overall, our survey was relatively equally distributed in terms of gender, with viable respondents comprised of 45 females (52%), 41 males (47%), and 1 non-binary/ other (1%). Utilizing occupational status to determine our expert grouping size, our sample contained 39 full-time employed individuals, 4 part-time, 3 retired, and 2 unemployed, reaching a total "expert" sample of 48 individuals. Looking at non-experts, or students, a total of 39 viable responses were received. In terms of age, our results skewed younger, which was expected when including the total viable response set, which has a reasonably high percentage of students (44%), when compared to the total sample. In terms of respondent primary residence location, this was largely dominated by individuals residing in Sweden, with 43 responses or approximately 49.4% of our sample. Immediately following with approximately 37.9% of our sample, or 33 responses, were individuals living within another EU country. Again, this could be expected, as dissemination occurred largely via personal networks, of which, most were primarily Swedish and European-based. Other responses collected from the USA (6), Asia-Pacific (3), and the Middle East/Africa (2) accounted for the remaining 12.6% of our sample.

When reviewing education, our sample largely consisted of a high proportion of respondents having completed graduate studies with 35.6% of respondents (31) having completed a master's degree and 29.9% of respondents (26) having completed a PhD. 26 respondents, or 29.9% had completed a bachelors-level education, and the remaining 4 responses had completed a primary-level education. Education fields were primarily comprised of Economics & Business Studies and Agriculture & Food with 39.1% (34 respondents) and 34.5% (30 respondents) respectively. The fields of education for the remaining respondents were Social Sciences (12.6%), Natural Sciences / Engineering (6.9%), Humanities (5.7%), or others (1.1%). Our sample was generally comprised of individuals employed within academia accounting for 66.7%, or 58 respondents, while those working within agriculture, both farming and non-farming accounted for 22.9%. The remaining 10.4% of respondents worked within Business and Administrative services or other industries.

5. Results

5.1 Introductory Evaluation

To begin our analysis, it was essential to familiarize ourselves with the collected data and summary statistics. As such, we first utilized a Shapiro-Wilk test to check for normality between the deviation of forecasts and real values. This test showcased a very large z-statistic (>12) and yielded a p-value of zero. Thereby we can conclude that our results are non-normally distributed, violating the assumption for parametric tests. This is of interest, especially when compared to a graphical illustration of the distribution of deviations, which appears to be relatively normally distributed, as seen in Figure 7, below.

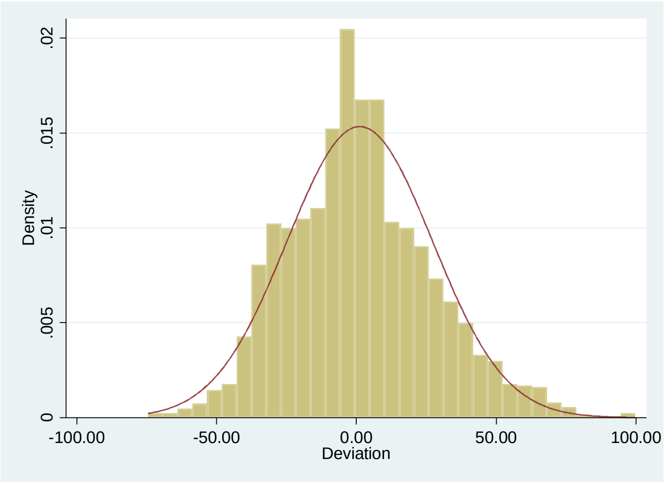

Figure 7: Distribution of percentage point deviation from gathered predictions against real percentage values

To adjust for socio-demographics and explore any potential sources of heterogeneity, we utilize a number of statistical analyses including (but not limited to) the Wilcoxon rank-sum test, median test, percentile ranges, and three differing variations of a linear regression.

5.2 Predictive Success Between Farmers & Consumers. Who is Easier to Predict?

As a primary goal in our research aims, we sought to better understand if one side of the agricultural system was easier to predict than the other. To determine this, we utilize a two-sample Wilcoxon rank-sum test (Mann-Whitney) to explore predictive accuracy via absolute deviation between forecasted and real values looking at both farmers and consumers. We complete this by looking at the level of expertise via occupational status. We employ this field as our survey pointedly targeted experts and students, thereby we should retain no other responses from outside these two groups. Inherently, we believe this showcases any existing biases, or if individuals (specifically experts) are more knowledgeable on either given side. We also utilize median tests and percentile ranges to verify and confirm any results from the Wilcoxon rank-sum.

Firstly, when reviewing the sample in its entirety (experts and non-experts) the Wilcoxon generates an extremely low p-value of 0.0014, thereby suggesting that the data is improbable under the null (at the 99% level) and leading us to believe there is significant difference in the distribution of forecasting accuracy between groups. Following this finding, we pare down our sample to review only industry experts (the full sample, minus those that have identified as students), for which we yield a rather high p-value of 0.4412, suggesting there is no evidence of difference. Given the relatively small sample in this instance, we cannot rule out a type II error (false negative) for medium or small differences. Interestingly, when looking at student forecasting between consumers and farmers, and utilizing the same methods (Wilcoxon rank-sum and median test), we find a statistically significant effect. In this situation, we yield a low p-value of 0.0005 and moderately high z-statistic of 3.5, thereby concluding that the data are unlikely to occur under the null at the 99% level and leading us to believe there is a difference in forecasts between groups for students.

Upon reviewing percentile ranges for the deviation in forecasting scores within the overall dataset, as well as for the student sub-grouping, we determine that for both, forecasts for farmers were more inaccurate when compared to forecasts for consumers. Reviewing the dataset for all responses, we calculate deviation percentiles of 18.94 and 15.92 within the 50% range for farmers and consumers, respectfully. Students showcased similar results, with deviations of 19.87 and 15.18, respectively, at the 50% level for farmers and consumers. Greater deviations present in the forecasts for farmer behavior leads us to believe that these predictions were more difficult for respondents when compared to the predictions given for consumer behavior. Utilizing similar parameters within the Median test, we are not able to discern if experts are better or worse at predicting either side of the agricultural system, while students are.

5.3 Impacts of other Heterogeneity on Forecast Accuracy

Utilizing three variations of a linear regression, we review the impacts of the inclusion of variables on our dependent variable, or the change in absolute deviation between real and forecasted values. Model 1 includes basic experimental data such as dummies for the scenario ID, the choice selected within the scenario, and the dummies for the order in which the scenarios and blocks were received by respondents. Model 2 expands to include respondent demographic information such as gender, occupation, industry, and education. Finally, Model 3 further includes variables such as confidence, self-perceived agricultural and economic knowledge, and reported difficulty. Coefficient estimates, which showcase the percentage point change in accuracy for the task, and the corresponding significance levels for primary variables within these three models may be found in Table 1.

Table 1: Regression models coefficient estimates on absolute deviation

Variable	**1**	**2**	**3**
Consumer Predictions	-2.55 (2.19)	-3.06 (2.20)	-3.32* (2.69)
Block Order	-1.42** (0.66)	-0.51 (0.73)	-0.77 (0.77)
Gender (Compared to female)			
Male		-0.18 (0.76)	-0.15 (0.83)
Prefer not to say		5.76* (3.20)	N/A
Occupation (compared to students)			
Full-Time Employed		-2.06** (1.03)	-3.49*** (1.11)
Part-Time Employed		0.48 (1.81)	0.17 (1.94)
Retired		-4.59** (2.06)	-4.49*** (2.13)
Unemployed		5.29** (2.41)	3.78 (2.51)
Industry (compared to academia)			
Administrative Services		-1.52 (2.28)	-3.16 (2.56)
Agriculture Farming		2.11* (1.15)	1.01 (1.28)
Agriculture Non-Farming		-1.14 (1.15)	-1.43 (1.23)

Consulting & Business Services		4.80***	4.03**
		(1.70)	(1.80)
Other		-2.37	-2.96
		(1.93)	(2.07)
Education (compared to PhD.)			
Primary School		-4.47**	-6.63***
		(2.01)	(2.28)
Bachelor’s Degree		-3.16**	-3.96***
		(1.30)	(1.38)
Master’s Degree		-2.83***	-2.86***
		(1.05)	(1.11)
Confidence			0.04*
			(0.02)
Difficulty (compared to extremely difficult)			
Somewhat easy			0.06
			(1.61)
Neither easy nor difficult			0.48
			(1.36)
Somewhat difficult			-1.70
			(1.33)
Agriculture Knowledge (compared to strongly agree)			
Somewhat Agree			1.23
			(1.23)
Neither Agree nor Disagree			-0.06
			(1.40)
Somewhat Disagree			2.63*
			(1.55)
Strongly Disagree			3.63*
			(1.99)
N	2,349	2,349	2,286
P-value	0.0000	0.0000	0.0000
R^2	0.0777	0.0911	0.0996
F	6.98	5.51	5.05
Adj. R^2	0.0666	0.0746	0.0799

Standard errors in parentheses; number of observations varies due to list-wise exclusion for missing values.

Note: * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.

It is important to note that, on average, respondents across the entirety of the sample displayed a 20.22 percentage point deviation for each task between their forecasted estimates, and that of the true values. This value will aid in adding additional perspective when discussing the deviation that variables had upon our dependent variable, forecast accuracy.

When reviewing the impacts of education on forecast success, our results showcase that those with a PhD were among the least accurate in their forecasts, compared to other education levels. Individuals with comparatively lower levels of completed education (master's degree, bachelor's degree, & primary school) showcased greater statistically significant accuracy in their forecasts at least the level of 95% significance (often the 99% level), as determined within our regression models 2 and 3. Interestingly, those with only a primary school education showcased the highest accuracy with a decrease in deviation by approximately 6.63 percentage points on average and a p-value of 0.004, when compared to those with a PhD. Those with the highest education at a bachelor's level performed similarly well, albeit with a slightly decreased accuracy, showcasing a decrease in forecast deviation by 3.96 percentage points on average and a p-value of 0.004. Those with a master's degree also performed better when compared to those with a PhD with a 2.86 percentage point decrease in deviation and a small p-value of 0.010.

Examining any potential impacts of profession on forecast accuracy, limited results were obtained. Reviewing both models 2 and 3, significant results showcase those working within the consulting or business services industry provided the lowest accuracy forecasts when compared to all other professions, including academia, agriculture non-farming, and agriculture farming.

Like that of comparable forecasting literature, we examine any potential impacts of self-perceived survey difficulty on our dependent variable; forecast accuracy. Our results, however, are unable to showcase any significant effect based on reported survey difficulty.

We also review any potential effects of confidence ratings on accuracy, as was also contained within much comparable literature. With a p-value smaller than the 1% threshold, we determined that for every unit increase in self-reported confidence, the deviation for accurate forecasts subsequently increased by approximately 0.04 units, ceteris paribus. This increase in deviation leads us to believe that those with higher self-reported confidence showcase lower predictive accuracy. While a relatively small increase, this finding is significant when compared to earlier forecasting literature, which does not always reach the same conclusions.

6. Discussion

6.1 Policy Implications and Practical Applications

While forecasting analyses remain largely understudied within food and agriculture, our findings present several unique points which may be discussed especially when compared to contextually limited, albeit existing, literature.

While we determine that experts do not necessarily provide more accurate forecasts, this contrasts with working papers by Schaak et al. (2023) and Rommel et al. (2022) which find experts (specifically those from academia) provide more accurate predictions on farmers' risk preferences when compared to other experts or students. However, it is important to note that the experts within these previous findings are comprised largely of international experimental economics researchers, and thereby do not include researchers from other fields, industry leaders, or others, potentially leading us to believe the performance of these alternative groups was less accurate. More importantly, experts in these surveys are tasked to predict research results based on abstract experiments, whereas in our case we are dealing with an intuitive straightforward task. In contrast to this literature, our research does not aim to pare down expert subgroupings and instead looks at a holistic level across the industry. While non-agriculture specific, comparable forecasting literature by DellaVigna & Pope (2018) reach similar conclusions as those discussed in Schaak et al. (2023). One such finding was that experts taken all together perform incredibly well, and overall, slightly better than those that are considered industry non-experts. This same study also found respondents perceived confidence levels were a clear indicator for predictive accuracy, in that higher confidence ascertained increased forecast accuracy across all 15 treatments. Our results, however, like that of Schaak et al.'s (2023), point to the inverse. Respondents who provided higher levels of confidence were found to have a decreased, albeit small, accuracy drop across treatments. It appears that our results, also comparable to that of Lambert et al.'s (2012) showcase that individuals that are familiar with an industry, especially experts, may be prone to overconfidence in their decision-making and forecasting. While the overall differentiation between our results and some previous studies could be ascertained via several reasons, one could expect the relatively large and diverse comparable sample size for these studies to play an influential factor in this conclusion.

Research by DellaVigna and Pope (2018) also showcases evidence of an inverse relationship between academic rank and forecasting accuracy, to which our results also point. Our findings similarly provide insights into a parallel relationship in that the highest forecast accuracy belonged to those whose highest level of education was at a primary school level. Contrary to expectations, those who had attained a PhD were among the lowest in forecasting accuracy for both farmers and consumers. This finding may be potentially explained via a relationship between effort and value of time. Seemingly individuals with higher academic accreditation may place a higher value on their time, and therefore put less time and effort into their responses. We must, however, point to potential impacts in this finding due to our relatively small sample size. With a final sample of 87 responses, impacts of randomness could be influencing this finding (among others), as our dataset contains approximately 21 individuals per educational group (primary, bachelor, master, and PhD). This value is especially small when we compare to related literature within prediction and forecast analysis studies.

While this work is limited in direct policy implications which may be ascertained, we make note of realms in which our results may be beneficial in a policy construct. Firstly, in the context of policy integrations via programs such as F2F, experts do not appear to be more knowledgeable or biased toward one side of the industry or another. We may surmise this to be beneficial for the potential success of policy integrations within the agriculture realm (such as F2F) if experts are heavily consulted, as there appears to be no bias in expert knowledge between farmers and consumers. We may also point to non-experts' ability to better forecast consumer behavior as equally telling. Extrapolating further, one may presume that consumers are not as aware of farmers' behavior or decisions, thereby hindering understanding and/or success of policy integrations. Our findings on the inverse relationship between education and forecast accuracy prove to be complex, but may also provide further insights into future research and policy, as generally, baseline assumptions believe higher education levels are generally tied with greater knowledge.

Remaining largely understudied, there remains great opportunity for similar forecasting literature within the realm of agriculture, and specifically agriculture economics. The peculiar lack of research in the expert prediction field may be attributed, in part, to a novel concept described within Gilbert et al. (2004), called the Region-beta paradox. This paradoxical consequence describes how individuals may often recover or alter their behavior more quickly for a highly distressing situation than they would for minor inconveniences. Psychologically, we are programmed to expect intense stressors will last longer than mild stressors.

Therefore, people generally only act upon the former, leaving the “mild stressor’ in its existing state. For example, an individual with a severe injury, like a broken leg, will generally take immediate steps to speed their recovery process, which they might not do for a minor injury, such as persistent knee pain. While both injuries cause challenges and remain treatable, the lower pain and lack of immediate consequence allow for the knee to remain unresolved. Similarly, in the context of this research, we may extrapolate that the repercussions of expert predictability (or lack thereof) are of consequence, but not at a high-enough level to warrant immediate action. Other, more important “stressors” will take precedence, as they likely remain more pertinent to researchers, industry, and the overall population. While it may be known that some experts do not align with others in their predictions or modeling, since the degree to which remains unknown there could be little incentive to explore the realm.

6.2 Limitations and Future Opportunities

As this is a relatively new field and scope of research for the agriculture industry, there are several areas in which we may improve future iterations of exploration in this context. Initially, in the beginning stages of our research creation, we determined the survey would remain fully anonymous, however, we would utilize trackable links to further differentiate between respondents. This was planned to be completed by delivering specific links to targeted groups such as students, academia distribution lists, or industry experts, as examples. However, following survey dissemination, it was discovered this function was no longer able to be utilized and therefore was non-operational. While this is relatively minor, consequentially we had decreased insights into the specific area of respondent’s expertise. Similarly, we have limited insights into the granular-level scope of experts who responded. While we can discern if these individuals were experts in academia, industry, economics, etc. we remain unable to determine the field of economics or industry these individuals are engaged in. For example, we are aware many respondents were experimental economists who are engaged within the agriculture industry (via the platforms links were shared), but we are unable to collate that information into our data. In this context, improvements may be made within future research or comparable investigations.

Further, we identify two potential challenges that may have arisen within the respondent base accessing our survey. Firstly, as we did not have any built-in screening to ensure target respondents were “experts”, there remained the possibility for non-experts or lay-people to provide a response and be recorded inaccurately. We do not believe this caused issue within our findings as the survey was not widely distributed in a public forum but was rather delivered to targeted groups via email requests and social media. However, we note the possibility remains and provides the possibility to present complications within future studies. Secondly, it remains possible that challenges arose via fraudulent machine-generated responses being collected from our survey. A total of 190 responses were collected upon the survey closing date, of which a strikingly large number appeared to be incomplete (100 responses). Upon further inspection, nearly the entirety of these 100 responses provided initial consent to the survey (multiple-choice format question) but were unable to answer further, subsequently leaving the survey open for an extended duration. Many of these responses were successfully able to opt-in to the survey on the primary opening screen but did not or were unable to progress further. It is conceivable that our survey was impacted by a malicious form of alias fraud, or machine-generated response via a robot (bot). We believe this potentially is possible due to one of two reasons: either (1) they were unable to navigate the multi-page structure of the survey, or (2) utilize the sliding bars which were employed within our forecasting structure. In total, approximately 50% of our responses were impacted by alias fraud. Comparatively, two recent agricultural-based studies analyzed by Goodrich et al. (2023) showcased fraudulent response rates of 96% and 72%, giving insights of ours to be on the lower end, comparatively speaking. In recent years as survey response rates have been declining, researchers have augmented the use of monetary incentives to attract additional participants (a mechanism that we also employed). In turn, this has subsequently led to an increase in the exploitation of surveys via participant fraud, alias fraud, or bots (Goodrich et al., 2023). While these responses could be a result of fraud, it remains possible that a number of our respondents chose not to progress further within the survey as a result of lengthy instructions, boredom, or a general lack of interest. While significant impacts were limited within our research, it necessitates the discussion of improvement within survey design and ensuring plans to mitigate fraud within future research.

Similarly, in the context of responses ascertained and collected, we believe improvements could be garnered from a larger sample size. While robust, our dataset remained relatively small, and our results may be bettered via a larger dataset. The context of our research relied heavily on the sharing of the survey link via personal networks, academic institutions, and research collaboratives. While this approach was beneficial in that we were mostly able to pre-select appropriate audiences to receive a request to participate, it was potentially a limiting factor in the dispersal of the survey to gather a large sample. With a final sample of 87 responses, this permits small counts within each of our variables (i.e. less than 20 individuals per educational group or occupation). Small variable counts such as this allow for an increased possibility of sampling error, as our respondent base may not be a truly representative sample. This becomes especially important when reviewing the impacts of covariance and correlation coefficients within our dataset.

Given such, we presume that a higher sample size would allow for a more stable and potentially unbiased sample.

Providing further potential for improvement in future studies is the showcasing or collection of perceived truthfulness of respondents in both the original DCE experiments, as well as forecasting-based research. As described by Cerroni et al. (2023), and Carson & Groves (2007) in some settings and/ or surveys, truthful responses are not always the optimal strategy and therein lead to a hypothetical bias. We must therefore contemplate if the stated preferences provided in the original experiments were indicative of true preference levels, or if there was any level of hypothetical bias present. The same could be added into the structure of a forecasting survey to collect the perceived truthfulness of respondents, allowing for a potentially more robust dataset.

Another potentially limiting factor that could have impacted results was the overall duration and complexity of the survey. The task conferred was likely unique from what respondents had previously faced, and therefore a large portion of time was spent reading directions to ensure the primary tasks were understood. The predictions given to respondents can be considered moderately difficult, and potentially time-consuming, when compared to other surveys respondents may have faced previously. Overall, the longer-than-average duration of the survey may have allowed for the influence of certain cognitive biases such as attention bias, decision fatigue, or cognitive overload. While we believe the effects of such were likely limited, we are unable to rule out any potential impacts. We do believe there is room for improvement within future iterations, most especially in the time required from respondents to complete the questionnaire.

Aside from discussed technical limitations or survey framework improvements, we believe the external validity across the greater agricultural or consumer sectors to be limited. The utilized DCEs are largely specific in their constructs and difficulty levels. For example, farmers responding to cattle grazing alterations were entirely composed of Swedish dairy farmers, which are likely non-representative of other farming groups, settings, or regions. Similarly, respondents answering consumer preference for dairy products were composed entirely of Swedish consumers, which may be more (or less) environmentally conscious or astute, with differing willingness to pay (WTP) as compared to consumers in other settings. While we may wish for this research to be extrapolated across the larger agri-producer and consumer industries, we believe this may not be achievable within this research scope and framework.

7. Conclusion

In this study, we analyzed predictive accuracy for consumer food decisions and farmer dairy cattle grazing preferences utilizing a novel prediction-based forecasting survey. A total of 2,349 prediction observations from 87 responses were collected and divided into treatments to study the impact of various respondent characters on their forecasting accuracy. Namely, these characteristics (variables) were composed of the status of expert vs non-expert, gender, education, occupation, industry, and agriculture/economics knowledge. This research and corresponding results are novel for the agriculture industry in three ways. Firstly, we collect straightforward predictions from respondents within the food and agriculture industry, which has been largely unexplored with this mechanism of research. Secondly, we showcase predictions on both farmers and consumers, covering both sides of the agricultural system. Lastly, we determine if levels of varying expertise have any impact on knowledge or forecast accuracy.

From our analysis, we gather no evidence that industry experts showcase greater levels of accuracy for either side of the agricultural system when compared to non-experts. Our results lead us to believe that within this context, experts are equally accurate in the predictive behaviors of farmers and consumers alike. We find relatively large statistically significant results suggesting an inverse relationship between education and increased forecast accuracy. Our results showcase the highest accuracy in predictions stemming from individuals with the lowest level of education, with decreased accuracy with each increasing level of higher education (bachelor's, master’s, PhD). Furthermore, we conclude that individuals with higher levels of education, such as a PhD, were overall less accurate in their predictions than individuals with a lower level of education, such as primary school. We additionally display results suggesting that individuals with higher levels of perceived confidence provided incrementally lower predictive accuracy across treatments.

As wealthy post-industrial societies around the globe seek to alter their food and agricultural systems with the aim of increased sustainability, future research such as this will become increasingly important. Topics such as the nitrogen mandates protested by Dutch farmers, discussions surrounding the efficacy of CAP, and the proper human diet to achieve environmental sustainability all showcase a need for expert engagement to aid in ensuring a viable path forward for all parties involved.

As food and agriculture systems become increasingly synchronized and integrated, expert knowledge will be heavily tested and relied upon. Likewise, the understanding of agricultural challenges faced by farmers, and decision processes for consumers will become of utmost importance for those who consume food, and those who raise it. Challenges in this mutual understanding may be seen within mentioned global headlines such as Dutch farmers' reactions to new agricultural mandates, research showcasing challenges and cost-effectiveness of the CAP, animal welfare initiatives and subsequent efficiencies, or sustainability-introduced required diet changes. Inherently, these headlines and corresponding policy initiatives are tangentially a result of a shifting agricultural system that seemingly aims to tie agricultural and consumer food policy as one. Further data on the knowledge of experts and other industry key players will likely prove crucial to outline the success, or subsequent failure of these programs, among others in the future, both near and far.

Contributing to the agriculture industry and predication-based analysis studies, this research expands into new territories for which comparable literature has not yet explored, helping to pave the way for future analysis and assessments.

8. Appendix

Table 2: Summary statistics consumer cheese DCE

	Row Labels	Count of id	Percentage
Cheese Choice Set 1	1	680	63.97
	2	230	21.64
	3	153	14.39
	Grand Total	**1063**	100.00
Cheese Choice Set 2	1	845	79.49
	2	186	17.50
	3	32	3.01
	Grand Total	**1063**	100.00
Cheese Choice Set 3	1	341	32.08
	2	707	66.51
	3	15	1.41
	Grand Total	**1063**	100.00
Cheese Choice Set 4	1	407	38.29
	2	194	18.25
	3	462	43.46
	Grand Total	**1063**	100.00
Cheese Choice Set 5	1	143	13.45
	2	544	51.18
	3	376	35.37
	Grand Total	**1063**	100.00
Cheese Choice Set 6	1	314	29.54
	2	564	53.06
	3	185	17.40
	Grand Total	**1063**	100.00
Cheese Choice Set 7	1	568	0.53
	2	235	0.22
	3	260	0.24
	Grand Total	**1063**	1.00
Cheese Choice Set 8	1	435	40.92
	2	574	54.00
	3	54	5.08
	Grand Total	**1063**	100.00
Cheese Choice Set 9	1	866	81.47
	2	151	14.21
	3	46	4.33
	Grand Total	**1063**	100.00
Cheese Choice Set 10	1	122	11.48
	2	541	50.89
	3	400	37.63
	Grand Total	**1063**	100.00

Table 3: Summary statistics consumer milk DCE

	Row Labels	Count of id	Percentage		Row Labels	Count of id	Percentage
Milk Choice Set 1	1	435	40.73	**Milk Choice Set 6**	1	877	82.12
	2	513	48.03		2	105	9.83
	3	120	11.24		3	86	8.05
	Grand Total	**1068**	100.00		**Grand Total**	**1068**	100.00
Milk Choice Set 2	1	254	23.78	**Milk Choice Set 7**	1	134	12.55
	2	796	74.53		2	665	62.27
	3	18	1.69		3	269	25.19
	Grand Total	**1068**	100.00		**Grand Total**	**1068**	100.00
Milk Choice Set 3	1	549	51.40	**Milk Choice Set 8**	1	679	63.58
	2	412	38.58		2	89	8.33
	3	107	10.02		3	300	28.09
	Grand Total	**1068**	100.00		**Grand Total**	**1068**	100.00
Milk Choice Set 4	1	583	54.59	**Milk Choice Set 9**	1	375	35.11
	2	467	43.73		2	390	36.52
	3	18	1.69		3	303	28.37
	Grand Total	**1068**	100.00		**Grand Total**	**1068**	100.00
Milk Choice Set 5	1	645	60.39	**Milk Choice Set 10**	1	73	6.84
	2	402	37.64		2	962	90.07
	3	21	1.97		3	33	3.09
	Grand Total	**1068**	100.00		**Grand Total**	**1068**	100.00

Table 4: Summary statistics farmer DCE

Farmer Choice Set 1

Row Labels	Count of id	Percentage
1	145	38.6667
2	98	26.1333
3	132	35.2000
Grand Total	**375**	100.0000

Farmer Choice Set 4

Row Labels	Count of id	Percentage
1	33	8.8000
2	250	66.6667
3	92	24.5333
Grand Total	**375**	100.0000

Farmer Choice Set 2

Row Labels	Count of id	Percentage
1	128	34.1333
2	120	32.0000
3	127	33.8667
Grand Total	**375**	100.0000

Farmer Choice Set 5

Row Labels	Count of id	Percentage
1	146	38.9333
2	76	20.2667
3	153	40.8000
Grand Total	**375**	100.0000

Farmer Choice Set 3

Row Labels	Count of id	Percentage
1	132	35.2000
2	125	33.3333
3	118	31.4667
Grand Total	**375**	100.0000

Farmer Choice Set 6

Row Labels	Count of id	Percentage
1	113	30.1333
2	125	33.3333
3	137	36.5333
Grand Total	**375**	100.0000

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