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Digital Agriculture and Digital Mining Entrepreneurial Policy in Saskatchewan: Global Entrepreneurship Monitor Expert Survey Data for Policy Analysis

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Executive Summary

Digital entrepreneurship is becoming an important element of regional economic dynamism. However, it varies significantly between regions, even within a single country, and there are few good indicators. Even more vague than the levels and importance of actual business activity are notions of policy relevance, success, and competence.

In 2015 and again in 2016 a team at the Johnson Shoyama Graduate School (JSGS) of Public Policy at the University of Saskatchewan asked 36 experts to provide their opinions on the framework conditions for digital entrepreneurship in the Province of Saskatchewan. The 2015 survey focused on digital entrepreneurship in Saskatchewan's agriculture cluster and the 2016 survey focused on the mining cluster. The collection methodology was in accordance with that used by the Global Entrepreneurship Monitor (GEM).

In the first part of this paper, we first scrutinise the standard ways in which GEM data from experts has been used and identify several significant problems: broad and uneven data distributions, data aggregation, and the level of analysis. The majority of the paper works through these problems and identifies a new type of analysis; a 'Likert bias' that compares the positive and negative bias in responses, that is able to overcome them.

In the second part of this paper, we apply this analysis to the data from our 2015 study of the agriculture cluster and 2016 study of the mining cluster in Saskatchewan. A Dunning-Kruger effect seems to operate some of the time, with experts most closely tied to their corresponding field having a tendency to provide more skeptical evaluations of their topic than experts from other fields. However, there also appears to be a 'ghost' in the data which is not always apparent where industry structure – fragmented (agriculture) vs consolidated (mining) might play a role. Dunning-Krueger effects are well known and hard to take into account when developing policy. The industry

structure feature is new to us in this form but may well also give another analytical tool for scrutinising policy actions and structures.

The final part of the paper summarizes the findings and implications. Overall, the Likert bias analysis is a useful tool for overcoming limitations of summary statistical analysis and allows us to see how different groups of experts view digital entrepreneurship in agriculture and mining. Views were found to differ significantly by expert group, suggesting the expert group, not the question group, is the appropriate level of analysis. There was also a degree of consistency in how groups of experts responded to different question groups, suggesting the GEM surveys could likely be simplified. The need to aggregate the positive and negative ends of the scales before meaningful interpretations can be made reinforces this. However, there were many cases where expert groups had both strong positive and negative opinions on a subject. The reasons why and implications of this are not clear from the survey data. Follow-up studies or a redesign of the GEM survey may be required to isolate the cause of this.

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Part 1: The GEM Expert Survey Data at *Cluster Level*

Aaron Hertes and Brian Wixted

1. Introduction

As part of a large Social Sciences and Humanities Research Council research partnership[1] the team at Johnson Shoyama Graduate School (JSGS) of Public Policy at the University of Saskatchewan investigated the speed, scale, and nature of the introduction of digital technologies in mining and agriculture. As well as looking to understand the transforming realities in the economic landscape we were also naturally interested in the contribution, or lack thereof, of public policy. The Global Entrepreneurship Monitor (GEM) platform is a globally proven vehicle for examining entrepreneurship. The National Expert Survey (NES) component of its methodology includes questions which examine the underlying conditions for entrepreneurship, and thus is well suited as a tool for our investigation. NES is administered online with an extensive and excellent range of questions with wording that has been honed from by large scale use since the late 1990s. It was thus perceived by us to be the best vehicle for our purposes. However, data from the NES has been only rarely deeply and then in ways that are not practically useful for policymakers in advanced economies. This chapter explores the problems with how the NES data has been used so far, and then describes the process by which we developed an approach to interpret the data which does not suffer these problems.

The first section of this chapter describes GEM and the NES methodology. The second section then sets out our arguments for why certain aspects of the NES methodology, and its application, are problematic. The third section presents the process by which we developed our

[1] https://munkschool.utoronto.ca/ipl/creating-digital-opportunity/

approach for analyzing the NES data, and the strengths and weaknesses of each stage. The fourth section discusses the strengths and weaknesses of our proposed approach, and its implications. The approach is applied to survey data from the agriculture and mining clusters in Saskatchewan in the following chapter.

2. The GEM Methodology

GEM is the world's foremost study of entrepreneurship. The project was established in 1999 to investigate why some countries appeared to be more entrepreneurial than others. With national teams collecting data in over 100 different economies, GEM examines the entrepreneurial behaviour and attitudes of individuals, as well as the national context in which they live to, gain an understanding of the entrepreneurial environments in different economies (GEM Consortium 2017c).

The GEM methodology includes two complementary data collection tools: The Adult Population Survey (APS) and the National Expert Survey (NES). The APS is a survey of a minimum of 2000 adults in each economy and is used to track the entrepreneurial attitudes, activities, and ambitions of individuals in those economies (GEM Consortium 2017a). The way in which data from the NES has been used is the focus of this paper and so it shall be described in more detail.

Unlike the APS, the NES is designed to capture details on factors which are believed to have a significant impact on entrepreneurship. These factors are known as Entrepreneurial Framework Conditions (EFCs) (GEM Consortium 2017a). EFCs include the resources, incentives, markets, and supporting institutions required for the creation and growth of firms and are considered essential to understanding business creation and growth[2].. While there are several other surveys which collect data analogous to several EFCs the NES was developed specifically to provide a harmonized measure which would allow for comparison between economies globally (GEM Consortium 2017d). In collecting data for the NES, national GEM teams survey at least four experts in each of the nine EFC categories, a minimum of thirty-six experts, in each GEM economy every year, who answer questions across all nine categories. The sample is not representative as respondents are selected by the research team on the basis of experience and specialization in their framework condition. The sample is not balanced for age or gender; the only restriction being that all geographic regions of the economy should be covered (GEM Consortium 2017b).

In the NES questionnaire, each EFC is represented by a nine-point Likert scale where 1 indicates the statement is "Completely False" and 9 is "Completely True." There are nine different EFCs with a varying number of questions in each category[3]:

[2] The approach by the GEM consortium has evolved and continues to evolve over time. In 1999 the NES designers selected several conditions through an exhaustive literature review because there were not tools measuring conditions that shape or make-up the context for entrepreneurship. At first, the NES tool (called Key informants at that time) included more than 9 topics, as for example: opinions on the level of opportunities perception, perceptions about entrepreneurial skills on the target populations, respect for intellectual property rights, and others. After some years and seeing that the participation of countries doing the NES was not regular because some argued that the questionnaire was too long, GEM focused on 9 conditions and discarded others that were covered by the APS survey. It is true that we lost the possibility of comparing the opinions of experts with the general population regard some topics, but at least, the NES survey could be continued as compulsory and providing homogeneous data on 9 conditions. It is important to note that the scales were extended up to 10 points which provide more variance and allow the application of more sophisticated statistical methods.

[3] In the GEM Consortium perspective each EFC is a latent variable or concept represented by a construct formed by items that are variables correlated with this concept and measured by a nine-point Likert scale were 1 indicates the statement is completely false and 9 is completely true. Once the data are collected, GEM applies principal components to these constructs that provide 12 latent concepts or EFCs. These variables are continuous between 1 and 9 points and the extreme values are interpreted as 1 "the average state of the condition is very insufficient" and 9 "the average state of the condition is very sufficient". For more information interested reader can look to https://www.gemconsortium.org/images/media/gem-neci-background-notes-1613753990.pdf which provides the NECI results for 2020.

1. *Entrepreneurial Finance:* The availability of financial resources (e.g. equity and debt) for small and medium enterprises (SMEs), including grants and subsidies.
2. *Government Policy:* The extent to which public policies support entrepreneurship. This EFC has two components. The first is entrepreneurship as a relevant economic issue, and the second is taxes or regulations that are size neutral or favourable to new businesses and SMEs.
3. *Government Entrepreneurship Programs:* The presence and quality of programs directly assisting SMEs at all levels of government.
4. *Entrepreneurship Education:* The extent to which training in creating or managing SMEs is incorporated within the education and training system at all levels. This EFC has two components. The first is the extent to which this training is present in the primary and secondary school levels, and the second is the extent to which it is present at post-secondary levels.
5. *Research and Development (R&D) Transfer:* The extent to which national research and development will lead to new commercial opportunities and is available to SMEs.
6. *Commercial and Legal Infrastructure:* The presence of property rights, commercial, accounting, and other legal and assessment services and institutions that support or promote SMEs.
7. *Internal market dynamics and entry Regulation:* This EFC contains two components. The first is market dynamics, which is the level of change in markets from year to year. The second is market openness, which is the extent to which new firms are free to enter existing markets.

8. *Physical Infrastructure:* Ease of access to physical resources (e.g. communication, utilities, transportation, land, or space) at a price that does not discriminate against SMEs.
9. *Cultural and Social Norms:* The extent to which cultural and social norms encourage or allow actions leading to new business methods or activities that can potentially increase personal wealth and income.

A tenth "special topic" is sometimes included. In the case of the 2015 and 2016 data collection, the special topic was "Senior Entrepreneurship." The questionnaire also contains several open-ended questions about institutional successes and constraints which foster or inhibit entrepreneurship in the (GEM Consortium 2017d).

While the GEM Consortium moves further and further away from the data in an attempt to construct indices and complex indicators beyond mere descriptive statistics through Principal Components Analysis, we remain unconvinced. The argument we develop here is this simply produces an answer when the mechanism for that answer becomes ever more cloaked. With years of policy experience, one of us (Wixted), is of the belief that policy makers would rather be able to see the engine of policy advice – in this case 'who believes what' – rather than have it hidden in a black box.

Though NES data is usually collected at the national level, it has also been used to collect data from sub-national regions. This is partially why GEM specifies that data is collected from economies[4] not from countries. The Canadian team has taken this a step further and collected data

[4] This is a standard approach by international organisations to avoid controversies for places such as Taiwan where sovereignty is disputed. However, NES has as we explain here largely analysed without cross referencing between layers of governance and policy control. The lack of access to economy reports due to language barriers makes investigating the topic even more problematic.

at the cluster level – a *Cluster* Expert Survey (CES) as opposed to the National and Provincial Expert Surveys.

Using CES data from 2015 and 2016, our team examined differences in entrepreneurial conditions specifically for *digital* entrepreneurship in the agricultural and mining clusters in Saskatchewan, respectively. The reasoning was that we could narrow down the context so specifically we could not only compare opinions between experts for the different clusters but also compare the responses to some of our research on the ground as to the adoption of digital technologies in these clusters. Within the context of GEM, we are not aware of others that have used the questionnaire in a cluster context.

3. The Problem

When we began our investigation, we reviewed previous publications to see how other researchers have used the NES data and found that much of it was presented in a way that is of little practical use to policy makers. What is more, it was often presented in a way which gives the impression that the authors do not consider it to be practical either. For example, the 2011 Australia Report and the 2015/16 Global Report devote only approximately a single page each to the analysis of NES data, with the Australia report going so far as to reduce their findings to a single sentence (GEM Australia 2011, 20, Global Entrepreneurship Monitor 2015/16 Global Report 2016, 30-31).

More recently, the use of expert survey data has been slowly but consistently expanding considerably. The Canadian report for the 2018 year and the Canadian 2019/2020 report show the pattern (Gregson, Saunders and Josty 2018, Gregson and Saunders 2020, Street and Saunders 2019). The 2020 Global report make more use of the data than previous reports (Bosma, et al. 2020). But a quote from the most recent Canadian report reveals the trouble with the black box approach. "Another question is to further examine the relationship between NECI scores or rankings, income group and entrepreneurial activity to determine more direct effects of framework conditions in the economy" (Gregson and Saunders 2020, 54). Canada performs well on some NECI comparison but not others, yet Canada is at the top of its group of countries in creating new entrepreneurial ventures.

Given that one of GEM's goals is to promote the use of this information as a basis for evidence-based entrepreneurship policy, this is a significant problem. The practical use of expert survey data appears to have three problems: the distribution of the data, the way the data is aggregated during analysis, and the level of analysis.

To assist with data analysis, GEM provides a Statistical Exploitation Manual for researchers to reference on its website as well as a new webinar (Coduras 2014). It suggests the use of frequency tables, pie and bar charts, and spider graphs for presentation of data, and the use of modes, medians, means, standard deviations, and "more sophisticated statistical analytical tools" (Coduras, GEM 2015 NES Statistical Exploitation Manual 2015, 97). The 2013 Global Report is a good example of how these methods were used in the past. It compares the *means*[5] of each Likert scale between economies to demonstrate interesting trends in the quality of EFCs as they relate to Factor-Driven, Efficiency-Driven, and Innovation-Driven economies[6], and also as they relate to different regions (Global Entrepreneurship Monitor 2013 Global Report 2013, 46-49). However, if the 2015 and 2016 CES data sets are to be taken as typical, then the data used in this report likely had a wide, uneven distribution. The implication of the distribution is that *means*,

[5] GEM refers to the expert survey data as continuous and therefore means as an appropriate analytical lens. However, while Likert data can be treated as continuous it isn't by nature and modes are still the globally preferred option.

[6] This classification developed by the World Economic Foundation (WEF) has now been abandoned in favour of the simpler but no less problematic macro world regions analysis (i.e., Europe and North America, Asia and Pacific etc).

regardless of whether standard deviations are included or not, cannot be taken as an accurate representation of the data. The problem of data distribution extends beyond the use of means and challenges other methods of analysis as well. We explore the problem of distribution further in the next section.

The second problem is the way the data is aggregated during analysis. There seem to be several contradictions between the way the NES methodology is theorized and the way it is practiced. The NES framework requires that experts with different backgrounds (e.g., finance, business, government) be surveyed, presumably because they each have a different type of knowledge to contribute. Yet during analysis, these groups are always aggregated together, and the means taken for the whole sample. It does not make sense that the NES should include different groups of expertise, deliberately selected on the basis of their differing expertise[7], only to then average all the data together and eliminate any nuance it might contain. A study by Lee and Wong (2006) used NES data found that there exist systematic differences in the way different actor groups perceive these issues. Therefore, the expert groups should not be aggregated during analysis. Rather, as we show in the next section, analyzing each expert group may be the way to make the NES into a useful policy tool; not as one for determining what *the* problem areas are, as GEM suggests it should be used for, but as a tool for determining *who* thinks *which* areas are problematic.

The third consideration we bring is that while GEM is a useful device for economies or provinces/states there is a tremendous opportunity to use expert surveys in tightly defined conditions – such as particular clusters or industries. Most NES data are collected at the national

[7] Our analysis takes this into account as much as practically possible, however it would be interesting to personally interview experts for their backgrounds and with that information examine their responses.

level. However, given the number of factors a respondent must consider when answering questions as they relate to an entire country, and the jurisdictional challenges of a country such as Canada, the amount of actionable information provided at such a level of analysis is very low. We argue that the narrower the level of analysis, the more meaningful and practically useful the information obtained will be. Thus, our analysis focuses on the cluster level, and our results show a high degree of differentiation between experts. This will be shown in the next section. GEM at the national or provincial levels should continue but we want to open possible use to very specific contexts and show the value of this particular expert survey in those.

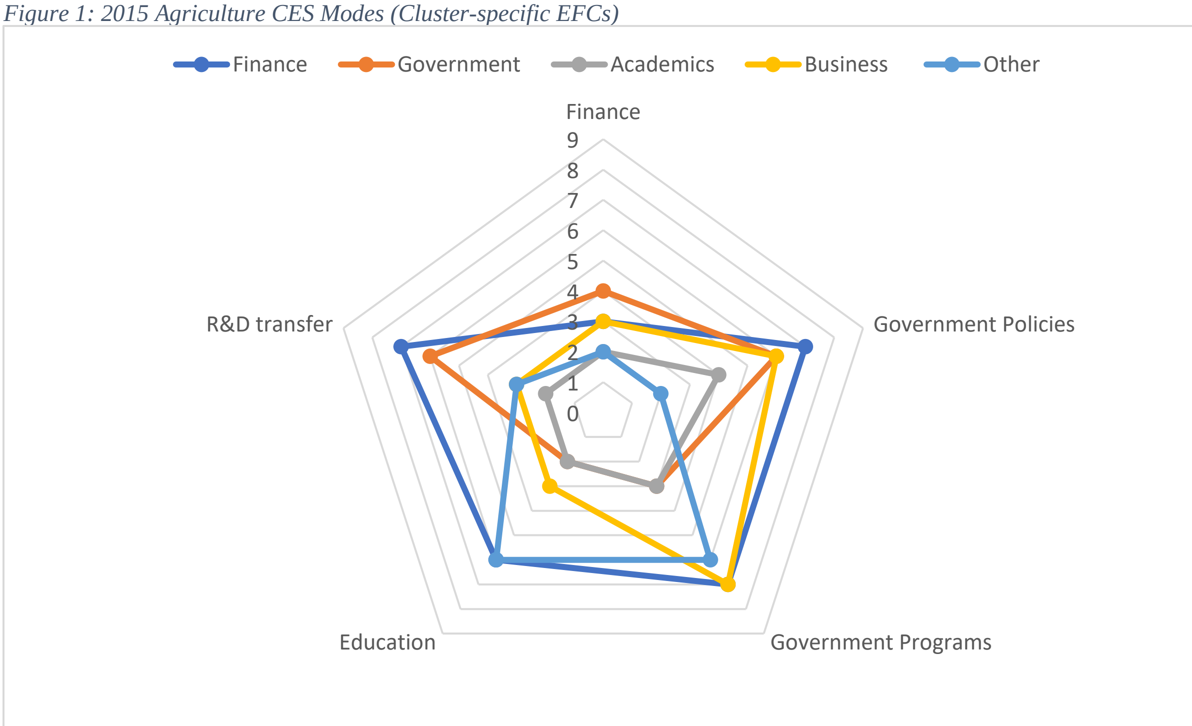
Having established data distribution, aggregation of experts, and the level of analysis as the three problem areas, the next section presents the steps taken to develop a method of analysis which does not suffer from these issues.

4. Analysis

To begin the analysis, the different experts were aggregated from nine categories down to five: Finance, Government, Academic, Business, and Other. Collapsing the expertise categories in this way attempts to best capture expertise without artificial boundaries while still maintaining the uniqueness of the category. As an example, instead of one category, government, there are two categories of expertise: government policy and government programs. Many senior government officials often have experience with both policy and programs, so it makes sense to aggregate those two categories into one. While finance and business might be perceived as similar, it was determined to leave these as separate due to the nature of the entrepreneurial finance specialisation.

The small sample size of each group restricts the method of analysis to descriptive statistics. Considering that means had been of only limited usefulness in previous reports, it was decided that the analysis would be done using modes as this method generally works well for attitudinal scales. We aggregated the responses from each expert group by EFC (finance, government policies, etc.) to facilitate analysis by expertise of response groups large enough to be at the bottom edge of meaningful. To explain, there might be four finance experts approached, each of whom answer nine questions on finance, providing a total of 36 responses (question topics vary in size). The *n* for government expertise will be typically around 8 and so forth.

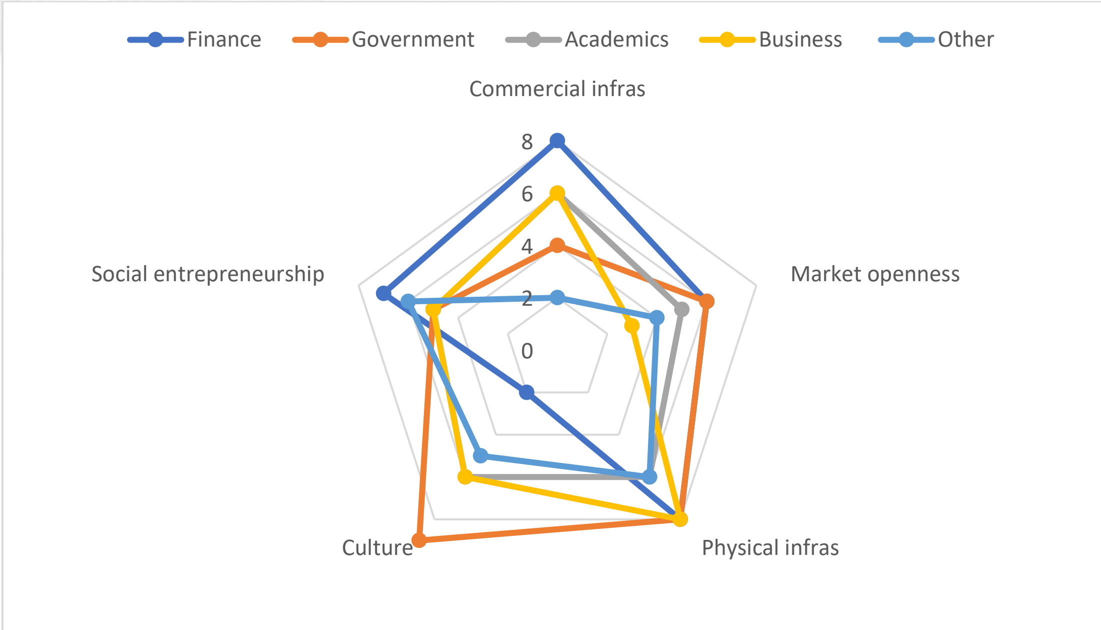
Figure 1: 2015 Agriculture CES Modes (Cluster-specific EFCs)



Figures 1 and 2 show the modes from the 2015 agriculture CES data set. We split the questions between cluster-specific and economy-generic EFCs such as the quality of physical infrastructure. Figure 1 presents the cluster-specific EFCs and displays several interesting patterns. First, it confirms the early hunch that experts with different expertise have quite different insights. Another pattern runs counterintuitively to organizational theory. Research on issue interpretation suggests that organizational factors influence the way respondents interpret certain issues and suggests that respondents tend to evaluate issues related to their self-interest in a way that is more favourable to them (Eden, et al. 1981, 38, Thomas, Shankster and Mathieu 1994, 1254, Lee and Wong 2006, 623). However, Figure 1 suggests that this might not always be the case. For example, the Finance, Business, and other groups display a much higher opinion of government programs than does the Government group; and every other group displays a higher evaluation of R&D Transfer than do Academics, the expert group which is believed to most closely align with that subject. Familiarity, and thus extensive knowledge of an issue, seems to bring to attention all the problems and less of the macro 'good' of a system. The Dunning-Kruger Effect (Kruger and Dunning 1999), which states both that those with less competence overestimate strengths and those with greater competence underestimate strengths, may best capture the phenomena here. However, given the Dunning-Krueger effect was only observed intermittently in both the 2015 and 2016 CES data, as well as in other GEM data sets, we are unable to provide strong evidence of such an effect using only descriptive statistics. This may be a fruitful area for future research that can apply analysis to larger data sets.

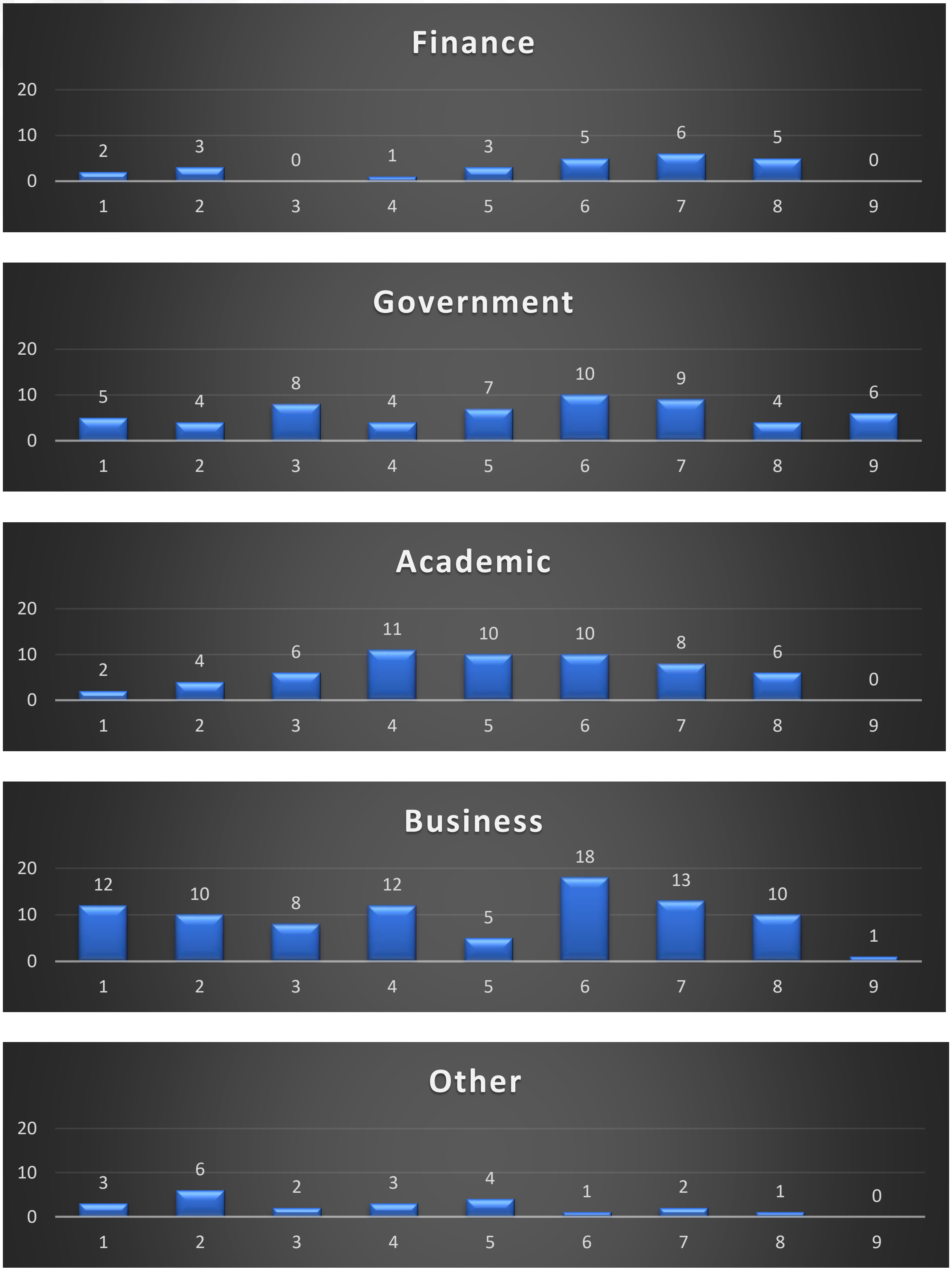
Figure 2 is the second half of the 2015 dataset and presents the results for the economy-generic EFCs. This second half to the questionnaire typically provides little insight for countries such as Canada or provinces such as Saskatchewan. Naturally, the Dunning-Krueger effect is not in operation here firstly because the questions are more generic and second because the prime focus of the analysis is the effect of these EFCs on entrepreneurship and not the quality of physical infrastructure or commercial infrastructure *per se*.

Figure 2: 2015 Agriculture CES Modes (Economy-generic EFCs)



While the analysis of modes allowed for easy comparison between groups, there was a problem in that the modes for each expert group in many of the data sets were very unstable. There were often either multiple modes, or a mode which was distinguished by only a single response. Figure 3 shows the frequency graphs for the responses to the Government Policy EFC questions in the 2015 CES data. This particular example does not have multiple modes, but it serves to show the instability in the frequencies. For the Finance group, the mode is 7, but if there was one response less, then 6, 7, and 8 would be tied for the mode with five responses each. The same is true in the Academic group. If the mode of 4 had one response less, then the distribution would become multimodal. Only the business experts give a response profile with robust modes. The academic response pattern is particularly problematic as the mode is on the negative side of the ledger yet more people provided positive answers than negative ones.

Figure 3: Frequencies for Government Policy EFC in 2015 Agriculture CES



This example demonstrates that, as with means, the mode could not be taken as an accurate representation of the data. With these options closed to us, we decided it would be worthwhile to create a series a frequency tables for each group's response to each EFC scale to get a better understanding of how the data was distributed, and so to determine how to work with it. Figures 4 to 9 are the frequency tables for the responses to individual questions in the Finance EFC from the 2016 CES data. The axis on the left side of the table corresponds to the Likert scale responses used in the survey (1 to 9). The axis on the top indicates the individual question within the EFC. The tables are shaded to reflect the different intensities of the counts according to the percent share of the total responses for the individual question. The ranges are Low (1-10%) (the lightest), Medium (11-20%), High (21-30%), and Very High (>30%) (the darkest). The two columns on the right show the counts and percent shares for the whole scale. Though this approach provides a much better understanding of how the data is distributed, above all it shows that analyzing the responses using every interval on the 1 to 9 scale is an unreliable method and that a different approach is required.

Table 1 is the Overall frequency distribution for the Finance EFC in the 2016 CES. Looking at the percent share column, we can see that though the agreement among experts on the conditions in Finance is relatively weak, there is a clear convergence between 2 and 6, with a concentration around 3. Observing the rest of the table, we can see that this pattern holds true for most of the questions individually. There are only two exceptions (questions 3 and 8) which seem to differ, though only slightly. However, though the overall distribution shows a moderate degree of consistency, examining each expert group individually reveals that they can contain a high degree of differentiation and shows why it is necessary to consider each question individually.

Table 1: Table Overall response frequencies for Finance EFC in 2016 Mining CES

	A01	A02	A03	A04	A05	A06	A07	A08		Number of Responses	Percent share
1	0	0	0	0	0	0	2	0	1	2	1
2	3	1	6	3	9	5	2	5	2	34	16
3	7	7	4	7	6	6	6	5	3	48	23
4	6	5	1	8	5	5	3	0	4	33	15
5	5	4	8	4	3	3	3	4	5	34	16
6	4	5	7	3	4	3	3	2	6	31	15
7	4	5	2	2	1	2	1	4	7	21	10
8	0	2	0	0	0	1	0	0	8	3	1
9	1	3	0	0	0	1	1	1	9	7	3
Total	30	32	28	27	28	26	21	21		213	

Table 2 presents the response frequencies from the Academic group, which is the closest match to the patterns in the Overall responses. The distribution is relatively narrow, falling between 2 and 6, and displays a convergence at 3. Moreover, the same pattern holds true for individual questions. For distributions such as this, modes and means would be adequate methods for reporting the results. However, Table 3 presents the frequencies for the Government group and underscores why modes and means are unsuitable for this analysis.

The distribution for the Government group ranges from 2 to 9 and shows little convergence in the responses. This holds true for individual questions as well, indicating little agreement among this group of experts on the state of Finance. Only two of the questions (4 and 5) show some degree of agreement, but many have only one or two values which have greater than a single response. Unlike the Academic group, the Government group bears little resemblance to the Overall distribution and shows why aggregate modes and means are unsuitable measures describing the data. Tables 4, 5, and 6 reinforce this, but in different ways.

Table 2: Academic response frequencies for Finance EFC in 2016 CES

	A01	A02	A03	A04	A05	A06	A07	A08		Number Responses	Percent share
1	0	0	0	0	0	0	0	0	1	0	0
2	1	0	4	1	3	2	1	2	2	14	27
3	4	3	2	3	2	3	3	3	3	23	45
4	2	2	0	2	0	2	0	0	4	8	16
5	0	0	1	0	0	0	1	1	5	3	6
6	0	2	0	0	1	0	0	0	6	3	6
7	0	0	0	0	0	0	0	0	7	0	0
8	0	0	0	0	0	0	0	0	8	0	0
9	0	0	0	0	0	0	0	0	9	0	0
Total	7	7	7	6	6	7	5	6		51	

Table 3: Government response frequencies for Finance EFC in 2016 Mining CES

	A01	A02	A03	A04	A05	A06	A07	A08		Number Responses	Percent share
1	0	0	0	0	0	0	0	0	1	0	0
2	1	0	1	0	3	2	1	2	2	10	18
3	2	1	1	2	1	2	1	1	3	11	20
4	2	1	1	3	1	1	1	0	4	10	18
5	2	2	1	0	1	0	1	2	5	9	16
6	1	1	1	1	2	1	2	1	6	10	18
7	0	1	1	1	0	1	0	0	7	4	7
8	0	1	0	0	0	0	0	0	8	1	2
9	0	1	0	0	0	0	0	0	9	1	2
Total	8	8	6	7	8	7	6	6		56	

Table 4:Business response frequencies for Finance EFC in 2016 Mining CES

	A01	A02	A03	A04	A05	A06	A07	A08		Number of Responses	Percent share
1	0	0	0	0	0	0	1	0	1	1	1
2	0	1	0	1	2	0	0	0	2	4	6
3	0	1	0	1	1	0	0	0	3	3	4
4	2	1	0	3	3	2	2	0	4	13	19
5	3	2	4	2	1	3	1	1	5	17	25
6	0	2	4	1	1	1	1	1	6	11	16
7	4	4	1	1	1	1	1	3	7	16	24
8	0	1	0	0	0	1	0	0	8	2	3
9	0	1	0	0	0	0	0	0	9	1	1
Total	9	13	9	9	9	8	6	5		68	

Whereas the Academic group displayed high levels of agreement both as a whole and for individual questions, and the Government group did not display high levels of agreement at any level, the Business group shows high levels of agreement for individual questions, but only a moderate level of agreement overall. In this case, any measures of the distribution as a whole would not adequately describe the nuance contained in the individual questions and could provide a picture entirely different from what the data actually contains.

A similar lesson can be observed for the Finance and Cultural groups in Table 5 and 6. Unlike for the Business group, these Figures serve to demonstrate the importance of sample size. Though both figures show moderate to high levels of agreement in some parts of the overall distribution, the small sample size means that a relatively high level of agreement can be achieved with only a few responses. These cases show that taking the frequencies for each of the 9 points on the scale cannot be considered a reliable representation of the group's sentiments, and that a reduction in the number of response categories is needed to analyze these data in a useful way.

Table 5: Finance response frequencies for Finance EFC in 2016 Mining CES

	A01	A02	A03	A04	A05	A06	A07	A08		Number of Responses	Percent share
1	0	0	0	0	0	0	1	0	1	1	4
2	1	0	1	1	0	1	0	1	2	5	19
3	1	2	0	1	2	1	1	0	3	8	30
4	0	1	0	0	1	0	0	0	4	2	7
5	0	0	2	1	1	0	0	0	5	4	15
6	1	0	1	0	0	0	0	0	6	2	7
7	0	0	0	0	0	0	0	0	7	0	0
8	0	0	0	0	0	0	0	0	8	0	0
9	1	1	0	0	0	1	1	1	9	5	19
Total	4	4	4	3	4	3	3	2		27	

In all, the frequency tables clarified two challenges presented by the data: How to present it in a simple way that would not be skewed by the distribution, and how to compensate for the small sample size in some groups. Up until now, the 9-point scale had been concerned with the *degree* to which expert opinion was positive or negative. However, this seemed to be the point from which the problems stemmed. We decided to try a new approach, aggregating the upper and lower end of the scale, and focussing only on the *percentage of positive versus negative responses* in each expert group; a method which proves to be both simple and effective.

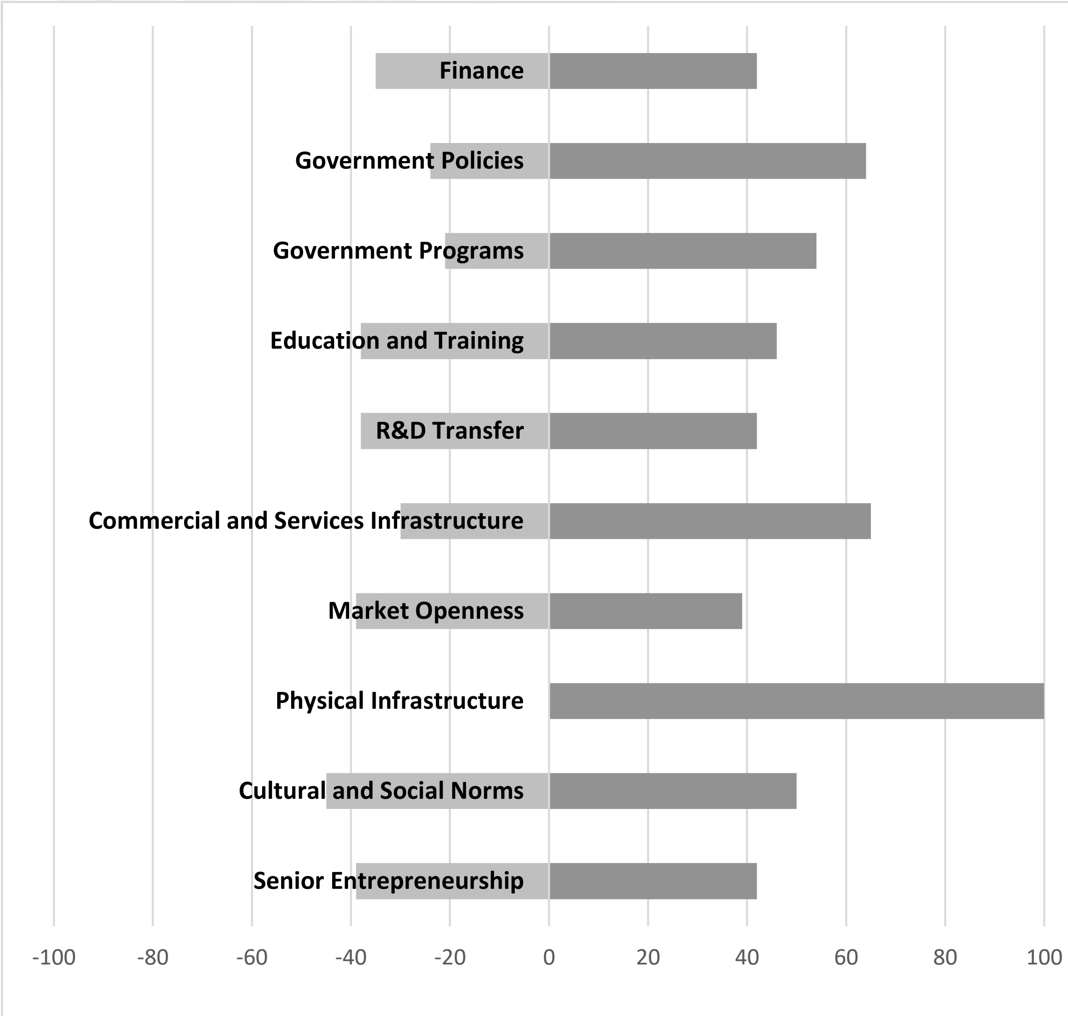
Table 6: Cultural response frequencies for Finance EFC in 2016 Mining CES

	A01	A02	A03	A04	A05	A06	A07	A08		Number of Responses	Percent share
1	0	0	0	0	0	0	0	0	1	0	0
2	0	0	0	0	1	0	0	0	2	1	9
3	0	0	1	0	0	0	1	1	3	3	27
4	0	0	0	0	0	0	0	0	4	0	0
5	0	0	0	1	0	0	0	0	5	1	9
6	2	0	1	1	0	1	0	0	6	5	45
7	0	0	0	0	0	0	0	1	7	1	9
8	0	0	0	0	0	0	0	0	8	0	0
9	0	0	0	0	0	0	0	0	9	0	0
Total	2	0	2	2	1	1	1	2		11	

5. *A way forward: The Likert "Bias" Analysis*

The final analysis we propose can be described as a *Likert bias analysis* as it compares the positive versus negative bias in the responses. Treating 5 as a neutral response/non-answer, the charts show the percentage of responses greater and less than 5. Excluding the 5 from the chart allows us to more easily visually compare the impressions that each expert group has of a specific EFC than other approaches such as percent bars. At the same time, it is not quite correct to say the 5 has been eliminated, as one can detect it by relative size of the bar compared to others within the group. Figures 4 and 5 presents the results of the analysis of the Finance expert group in both the 2015 and 2016 CES data which measures the conditions for digital entrepreneurship in agriculture and mining, respectively. In the discussion that follows we develop the proposal based on a single expert group. An analysis that compares all the expert groups appears in the following chapter.

Figure 4: Likert Bias Chart for Finance Experts, 2015 Agriculture CES



Using this Likert Bias Analysis, we can quickly visualize which side of the fence various experts are sitting. For agriculture (Figure 4), the finance experts are almost evenly split on whether finance for agricultural digital entrepreneurship is in the positive or negative zone but are more positive than negative. These experts believe government policy settings are good and also positive about government programs. Opinions about R&D transfer are almost evenly split again.

We can show the benefit of the analysis we have developed here with the aid of the actual numbers in the format of modes, means and our bias analysis Table 7. Curiously, and this is the point, the mode for the finance experts for digital agriculture (Table 7) is negative, and even the mean is just 5. Yet when we analyse the percentage of responses above and below 5 there is actually a bias to indicating that there are favourable conditions. With a small n, and a wide dispersal of answers we think this shows the value of considering what we have called the bias analysis.

Table 7: Modes and Means for Finance Experts in 2015 Agriculture CES

	Result
Mode	3 (negative)
Mean	5 (mid point)
Bias Positive (>5%)	51%
Bias Negative (<5%)	37%

If we turn our attention to mining (Figure 5) the benefit of this 'bias' analysis shines through. Finance experts clearly believe on the whole that finance, government policies and government programs are not beneficial to digital entrepreneurship in mining. We can see in Table 8 that both the mode and mean for mining are negative but it is only with the bias analysis that the true shape can be understood. There is a very strong negative sentiment for digital entrepreneurship in the mining cluster.

Figure 5 : Likert Bias Chart for Finance Experts, 2016 Mining CES

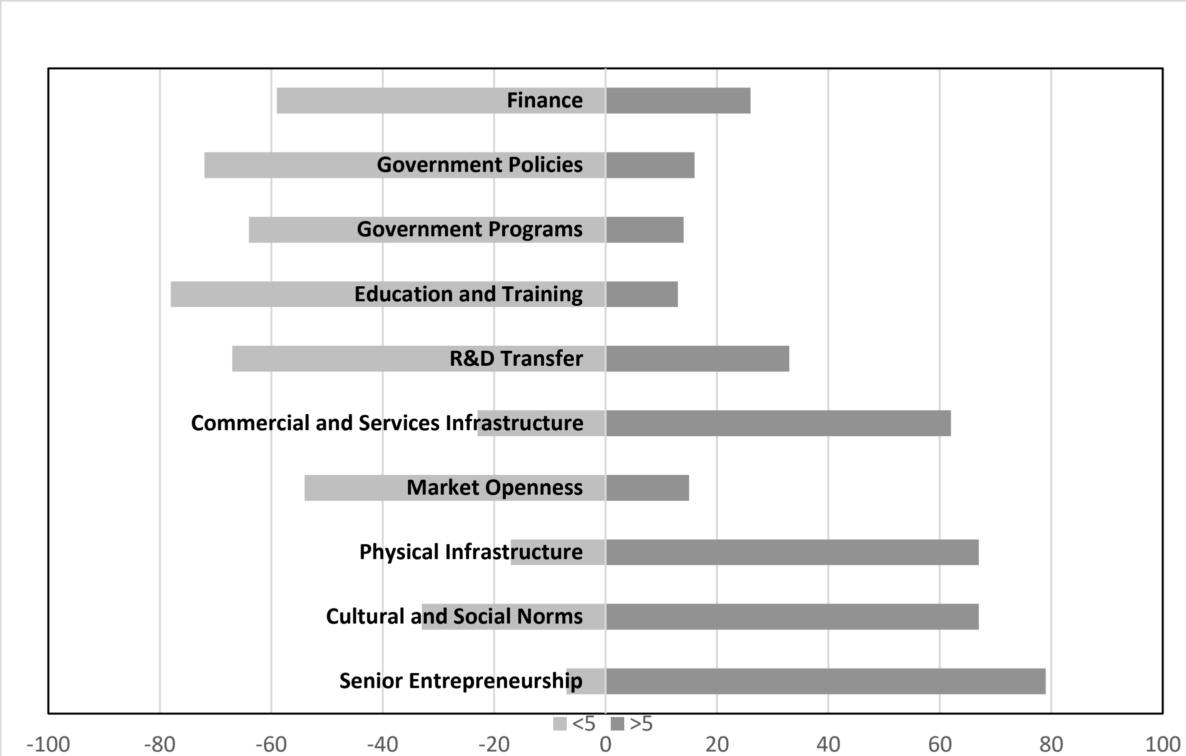


Table 8: Modes and Means for Finance Experts in 2016 Mining CES

	Result
Mode	3 (negative)
Mean	4 (negative)
Bias positive (>5)	26%
Bias negative (<5)	59%

We thus have a very clear picture from the analysis: the finance experts believe the conditions for digital entrepreneurship in agriculture are much better than those in mining for digital in Saskatchewan, yet traditional analysis would not indicate this. Having developed a methodology we believe can actually reveal the attitudes of the respondents more clearly, we can move onto present the results of the two cluster studies.

Part 2: Policy Analysis

Brian Wixted

Our focus in this chapter is to compare the opinions of different expert groups against one another to understand both what the experts think of the cluster conditions but also learning about how different expert groups perceive the issues. In public policy, “perception” is often as important as “reality.” It is therefore often useful to determine which areas are viewed as problematic by different groups. The Likert bias analysis developed in the previous chapter is well-suited to this task.

The subsequent analyses present the responses for different expert groups in each EFC. The data is collected from different experts across the 2015 agriculture CES and the 2016 mining CES with the focus on digital entrepreneurship.

1. Entrepreneurial Framework Conditions: Finance

Figure 6 quickly makes it apparent that most expert groups believe that the finance conditions for digital entrepreneurship *in agriculture* are poor. The exception is, curiously, the finance experts. Academics, perhaps the group furthest from direct knowledge have the lowest opinion of the conditions.

Figure 6: Finance conditions for digital entrepreneurship, 2015 Agriculture CES

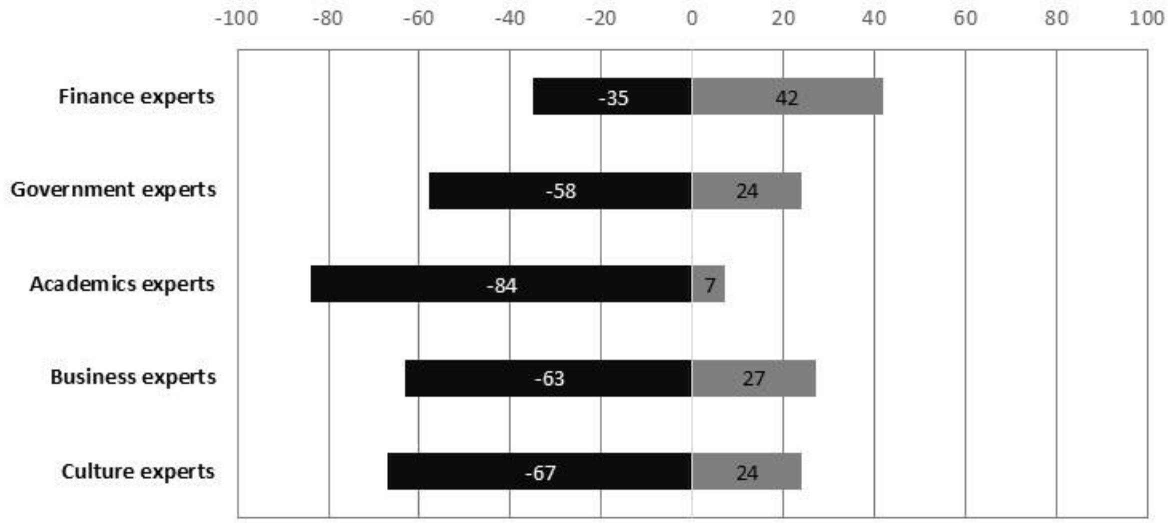
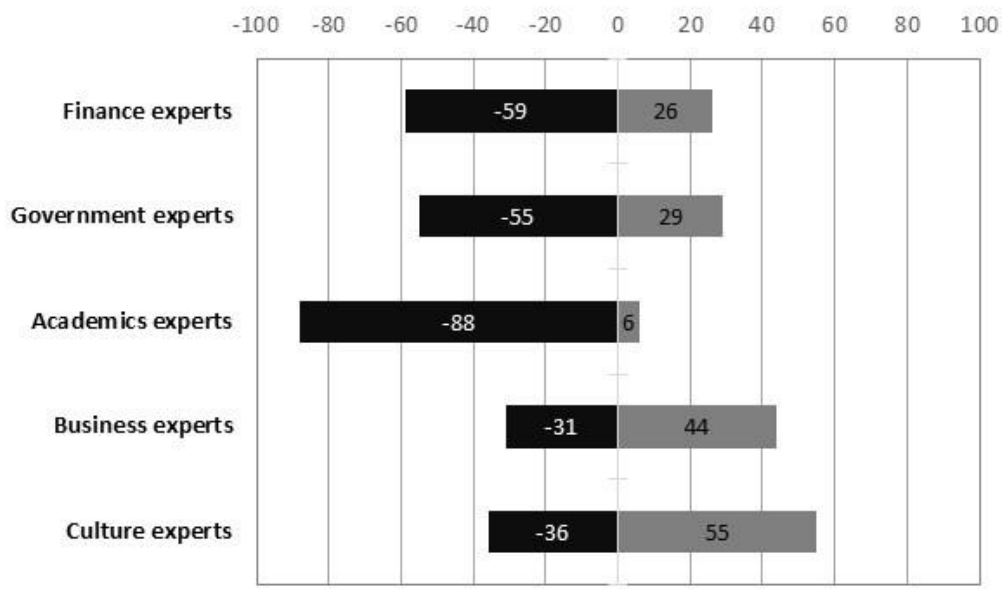


Figure 7: Finance conditions for digital entrepreneurship, 2016 Mining CES



For the mining sector (Figure 7) finance experts are more negative than for agricultural sector. Government experts are slightly more optimistic about mining than for agriculture, but still negative. Academic experts have similarly negative opinions to those that academics expressed the previous year for agriculture. Both business and culture experts are very much more positive about finance in mining.

Table 9 shows a quick comparison of the level of *positive and negative opinions* expressed provides an interesting indicator of sentiments. The highlighted cells indicate where 40 per cent or more of the opinions in an expert group are positive. We can quickly grasp that only finance experts thought that finance conditions in agriculture were at our benchmark level. By contrast, business and culture experts thought mining offered good prospects.

Table 9: Finance conditions – Positive and negative responses (% of total responses)

	Positive		Negative	
	Agriculture	Mining	Agriculture	Mining
Finance experts	42	26	35	59
Government experts	24	29	58	55
Academics experts	7	6	84	88
Business experts	27	44	63	31
Culture experts	24	55	67	36

Highlighted = above 40 per cent. In this data there is symmetry with no bimodal examples.

2. *Entrepreneurial Framework Conditions: Government Policies*

Most expert groups are strongly positive about government policies for agriculture (Figure 8). Interestingly, government, academic and business experts express almost as strong negative opinions. This suggests a lack of agreement within the expert group. Further research would be needed to determine the nature of this disagreement. Only the culture experts had a decidedly negative view.

Figure 8: Government policies for digital entrepreneurship, 2015 Agriculture CES

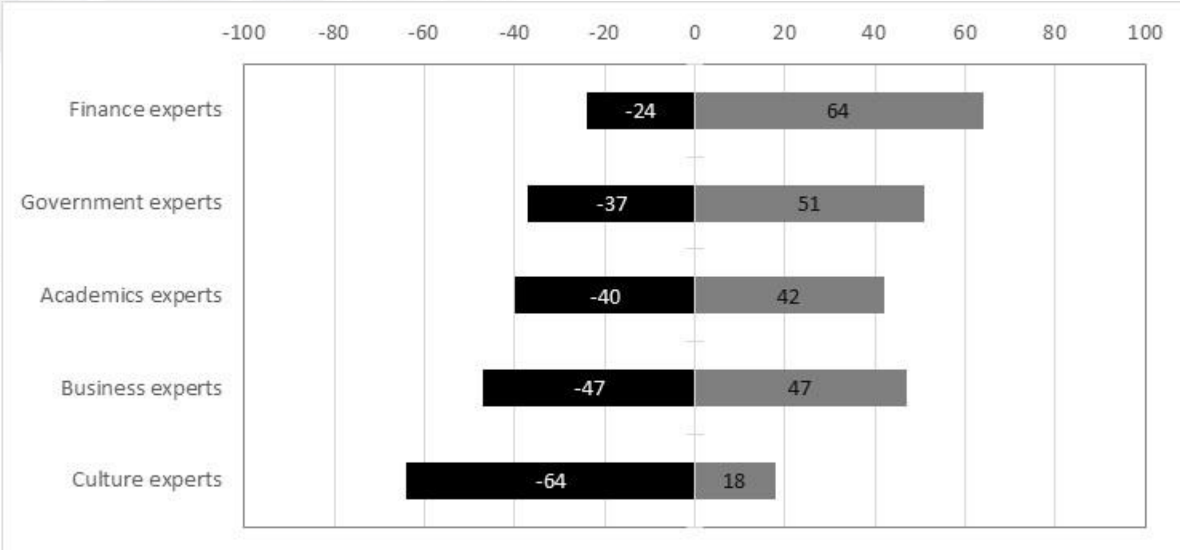
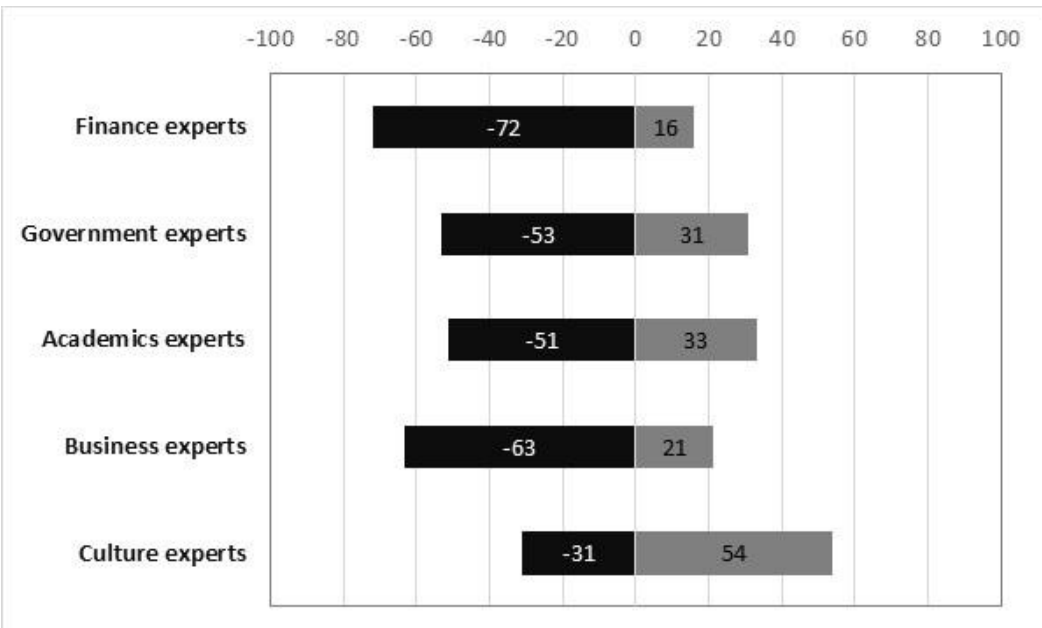


Figure 9: Government policies for digital entrepreneurship, 2016 Mining CES



The converse is weakly true of the mining sector (Figure 9). All except the culture experts were less optimistic about government policies in mining than they were for agriculture.

Table 10: Government policy conditions – Positive and negative responses (% of total responses)

	Positive		Negative	
	Agriculture	Mining	Agriculture	Mining
Finance experts	64	16	24	72
Government experts	51	31	37	53
Academics experts	42	33	40	51
Business experts	47	21	47	63
Culture experts	18	54	64	31

Highlighted = above 40 per cent. In this data there is split opinions by academics and business experts in the agricultural space.

The conclusion is that government policies towards agriculture based digital entrepreneurship were supportive, but the mining sector policies were not as encouraging. However, more than a third of the government people and academics were positive about mining (Table 10).

3. *Entrepreneurial Framework Conditions: Government Programs*

Separating policies and programs probably equates to differentiating the general climate in government from the cold hard cash of government actions for the different sectors. On the basis of responses for we have observed so far, it should not be a surprise that most expert groups expressed reasonably strong positive attitudes towards government programs in the in the agriculture sector (Figure 10). Government experts reveal an even split. Another result that emphasises our methodology.

Figure 10: Government programs for digital entrepreneurship, 2015 Agriculture CES

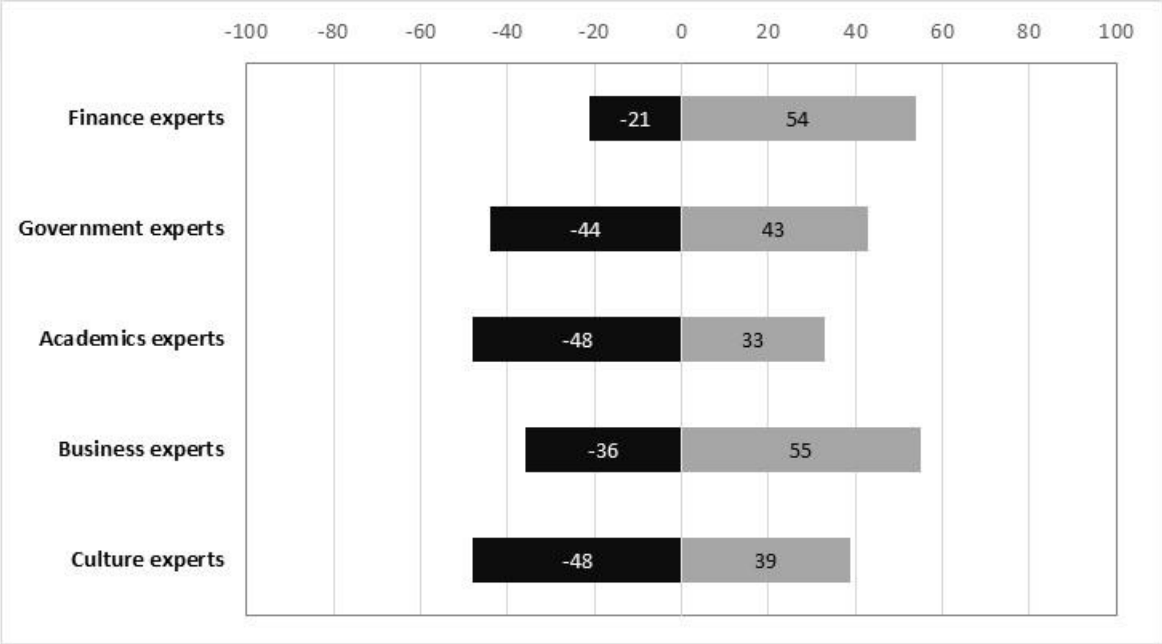
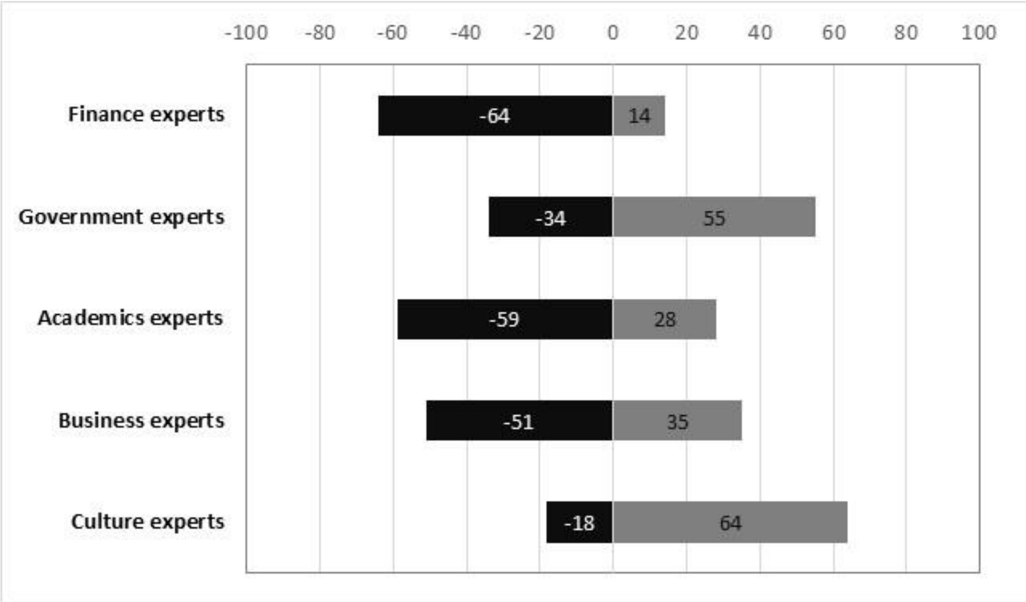


Figure 11: Government programs for digital entrepreneurship, 2016 Mining CES



There is a significant surprise however (Figure 11) with government experts expressing strong positive attitudes towards government programs for mining digital entrepreneurship. Contrast this to the view that government policies were viewed negatively. Thus, the conclusion to draw is government experts do not believe that government policies support digital entrepreneurship in mining, but the cash does. Again, the culture experts view the mining sector more positively than agriculture, which again is out of step with the other expertise categories. It would be fair to say the finance experts actually expressed concern with government programs given 64 per cent of responses were in negative territory. The comparison of positive responses in Table 11 makes the profile clearer.

Table 11: Government programs conditions – Positive and negative responses (% of total responses)

	Positive		Negative	
	Agriculture	Mining	Agriculture	Mining
Finance experts	54	14	21	64
Government experts	43	55	44	34
Academics experts	33	28	48	59
Business experts	55	35	36	51
Culture experts	39	64	48	18

4. *Entrepreneurial Framework Conditions: Education*

As with the Finance EFC, the finance, government, and cultural experts were divided on whether the education system was supportive. This was not the case for academics and business experts, both we would suggest are the closest to the action, were decidedly negative.

Figure 12: Education system conditions for digital entrepreneurship, 2015 Agriculture CES

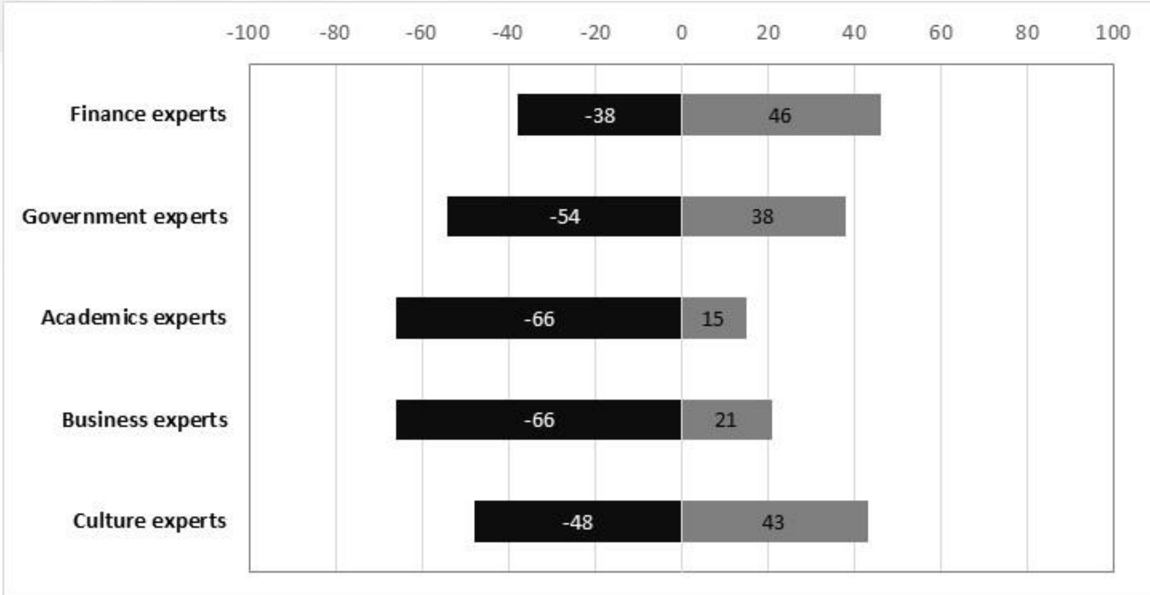
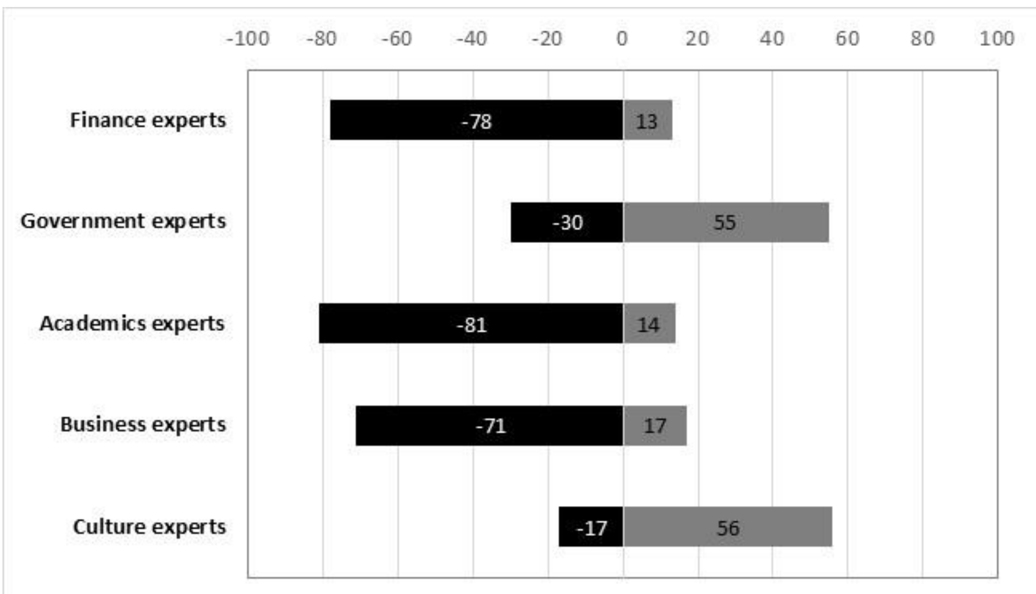


Figure 13: Education system conditions for digital entrepreneurship, 2016 Mining CES



For mining, government experts and cultural experts thought the education system was favourable to digital entrepreneurship (Figure 13). But these groups were very much out of step with other experts. This can be seen in Table 13.

Table 12: Education system conditions – Positive and negative responses (% of total responses)

	Positive		Negative	
	Agriculture	Mining	Agriculture	Mining
Finance experts	46	13	38	78
Government experts	38	55	54	30
Academics experts	15	14	66	81
Business experts	21	17	66	71
Culture experts	43	56	48	17

At this point, it is worth highlighting something interesting. Government experts had by a small margin, more favourable opinions of *finance* in mining than agriculture (though both were biased to the negative generally). The same group thought that agriculture had a stronger policy base, yet the programs were better for mining than agriculture. Further, mining had a better education system. Unexpectedly there is not a consistent thread running through the results.

5. ***Entrepreneurial Framework Conditions: R&D Transfer***

The results for R&D transfer in agriculture are curious (Figure 14). On the positive side, finance, government, and business expert groups are at or close to our rough significance benchmark of 40 per cent. At the same time, all expert groups are also strongly negative about the system as well. This suggests that there is even more disagreement among experts regarding R&D transfer than there was for finance.

Figure 14: R&D transfer conditions for digital entrepreneurship, 2015 Agriculture CES

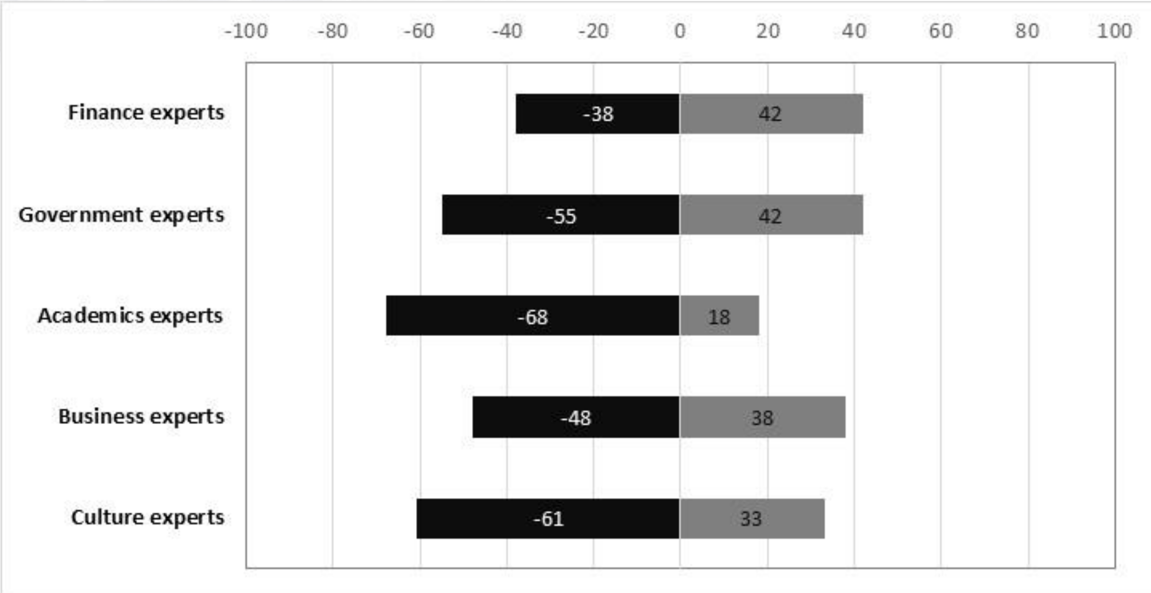
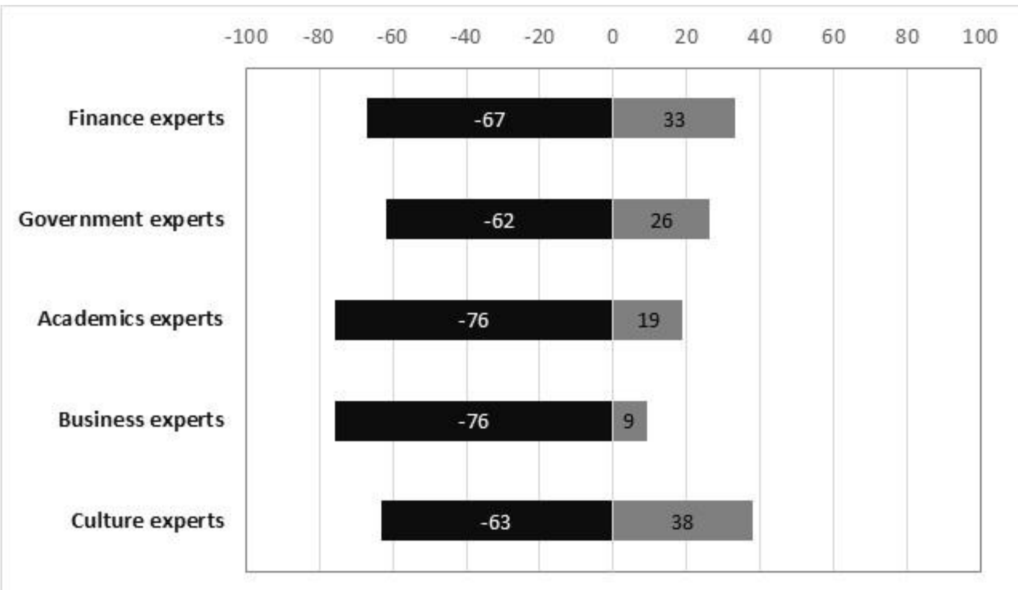


Figure 15: R&D transfer conditions for digital entrepreneurship, 2016 mining CES



There is no bi-polar division when it comes to mining, except for the cultural group which comes close (Figure 15). The strongly negative sentiment is obvious to everyone. It is worth again highlighting that the culture experts have been consistently out of step with their support for conditions in the mining systems.

Table 13: R&D transfer conditions – Positive and negative responses (% of total responses)

	Positive		Negative	
	Agriculture	Mining	Agriculture	Mining
Finance experts	42	33	38	67
Government experts	42	26	55	62
Academics experts	18	19	68	76
Business experts	38	9	48	76
Culture experts	33	38	61	63

6. *Upwards and Downwards Bias of respondents*

All of this raises the question, do groups generally have favourable opinions about particular sectors? When we compare the positive scores across the board, we can observe a certain consistency (Figure 16). Finance experts are generally the most positive towards agriculture. Only once was another group more positive - business experts in the question group of government programs. Business experts generally were more variable, ranging from relatively strong positive views for government programs and commercial services and those less positive views for education and training and market openness. Academics were the most negative, except in the case of commercial infrastructure. This of course leaves the government experts somewhere in the middle.

Figure 16: Agriculture (2015) percentage of positive scores by expert group

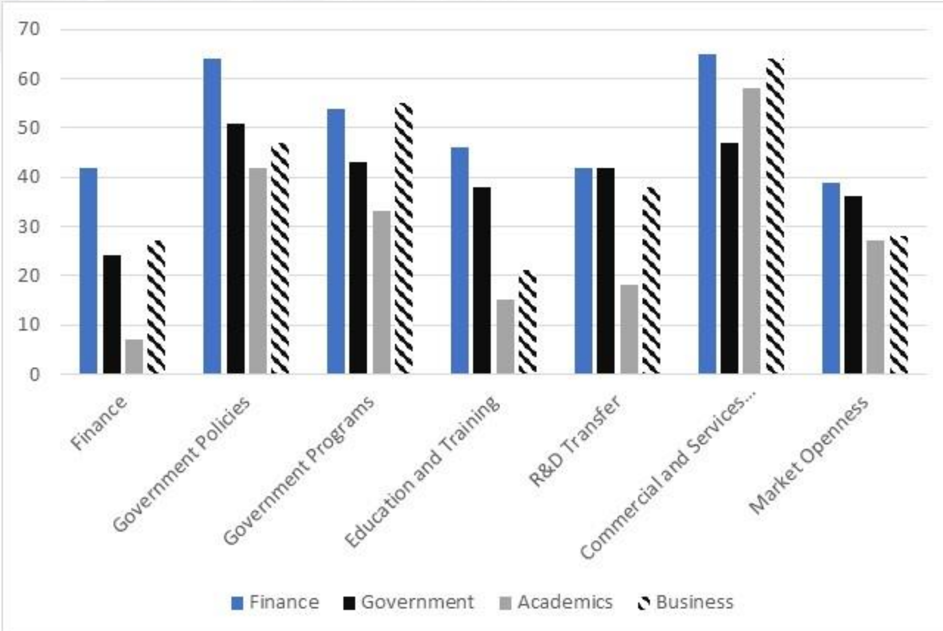
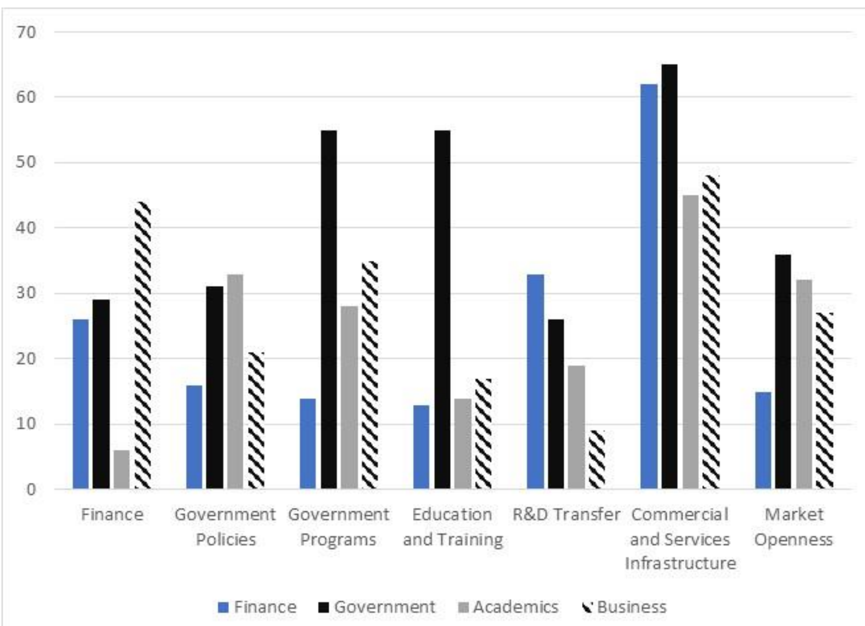


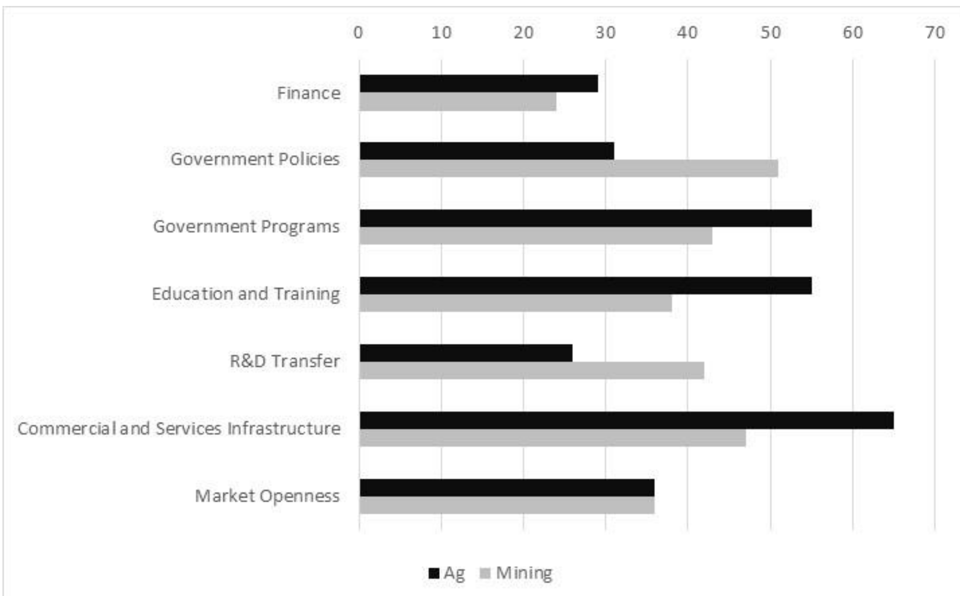
Figure 17: Mining (2016) percentage of positive scores by expert group



It might have been a surprising result that in 2015 finance experts were the optimistic bunch for agricultural digital entrepreneurship. That did not carry over to mining (Figure 17). Their view relative to the other experts was much more suppressed. There is another surprise when we do the comparison this way. The government experts were relatively high for finance, government policies, government programs, education system, commercial infrastructure and market openness, but this is surprising because they overall tended to be more strongly negative than positive.

It is worth, honing in then on the government experts a bit more closely (Figure 18).

Figure 18: Government experts – agriculture and mining directly compared (positive bias results)



When the positive results for government experts are directly compared between agriculture and mining, we can see that this group consistently regarded agriculture more positively than mining except in the cases of government policies and R&D transfer.

Conclusions

One speculation regarding the profile of the results is that because mining is a cohesive sector and dominated by a few companies that make significant contributions to government revenues there could be a general mental bias that it should be okay. The results of the cultural experts in favour of mining are suggestive of a provincial cultural bias in favour of *mining as an* *economic engine*. In all five framework conditions analysed here, culture experts rated conditions in mining better than agriculture. But the question was not whether the general conditions in Saskatchewan favour mining. The question was whether there were good conditions for *digital* entrepreneurship.

Part 3: What Can We Learn?

Brian Wixted and Aaron Hertes

The GEM expert survey is an impressive online tool that should, we believe, be used more widely than the typical context of the annual GEM survey cycle of economies. In particular through the exercise presented here, it can generate interesting data for cluster analysis. However, where we diverge is we think looking at the how the expert groups respond rather than black boxing the data provides invaluable insights.

1. Reality vs Perception revisited.

To wrap up this discussion of the expert survey analysis we can ask, where did the bias of the expert group go in their fields of specialty?[8]

Table 14: Expertise 'homefield' views (benchmarks – above 40%)

	Agriculture Positive	Agriculture Negative	Mining Positive	Mining Negative
Finance experts	☒			☒
Government experts (policies)	☒			☒
Government experts (programs)	☒	☒	☒	
Academics experts (education)		☒		☒
Academics experts (R&D Transfer)		☒		☒
Business experts (R&D Transfer)		☒		☒

[8] Note we have not analysed cultural issues in this paper.

We can not claim to have vast knowledge of the real entrepreneurial conditions in either agriculture or mining. However, over the five years of the Creating Digital Opportunity SSHRC funded research partnership[9] (2014-2019), one observation has stood out above others. Across the Canadian prairies there is some excitement about the possibilities for agriculture based digital entrepreneurship. The level of change in the acceptance of advance machinery in this sector is breath-taking. Some of these findings are included in the analysis of the different digital ecosystems emerging in agriculture[10]. In contrast, we have observed no significant activity in the mining sector whatsoever – not to put too fine a point on it[11]. Therefore, in broadbrush terms the results for agriculture are interesting and probably the basis for further serious discussions. The results for mining were somewhat concerning.

2. *Overview of findings*

GEM expert survey data is usually combined with the survey of actual entrepreneurial activity. This holds the expert perception data to some sort of reality check. However, the expert data holds the potential for greater use.

Our analysis reveals that the data analysed in traditional descriptive ways hides results because there is a clear problem whereby modes and means (do not capture the layers of views expressed. Further, we want data that that could be the basis of conversation with policy makers.

To overcome this, we developed the Likert Bias analysis to see the views express <5 and > 5. This helps us visualise more clearly the bias of opinions. The Likert Bias Analysis clearly

[9] https://munkschool.utoronto.ca/ipl/research/creating-digital-opportunity/
[10] Phillips 2019.
[11] See Wixted 2019 on the Australian uptake of autonomous machinery and big data analytics.

reveals that views differ significantly by expert group and suggests analysis should therefore be by expert group not just question group. We also found that expert groups often have consistent views through the question groups. This may indicate that surveys could and probably should be simplified.

This study added another innovation by using clusters as the level of analysis. This improved on previous studies as the results reflected a more tangible reality than more abstract "economies." Even so the dispersal of opinions is often huge and often there are equally strong opinions in both negative and positive directions. This indicates while surveys could be simplified another factor is at play in the background and surveys need to be designed to pick up on these.

Though not quite a finding, three notable features of the data that merit future investigation were the possible existence of a Dunning-Kreuger effect analog, a seeming positive bias to the more coherent mining cluster, and a certain consistency in the response patterns of different expert groups. This latter case may suggest a general skepticism/optimism or may indicate some knowledge that is not reflected in the survey data.

We are interested in understanding the differences in the digital entrepreneurial potential of the Canadian agriculture and mining industries, two natural resource-based clusters. Globally, there is significant dynamism in these activities which is driven by new digital technologies. The GEM platform is a globally proven vehicle for examining entrepreneurship, and the NES component of its methodology has the potential to provide insight into these clusters. However, the ways in which the NES data have been used are of little use from a policy perspective. This paper presented the stages by which we arrived at an approach which provides the clarity needed for this data to be of practical use. The Likert Bias Charts display a clear pattern of how experts generally view the EFCs within two cluster examples and allow for a high degree of differentiation, and thus comparability, between clusters.

What these results absolutely reveal is that sector of interest and the field of expertise matter when it comes to policy analysis. If we want to focus on policy matters, we need to zoom in and ask how experts understand various entrepreneurial framework conditions. Further, there are hints in these results that the structure of industries, whether fragmented or consolidated may affect the impression and impression can be important when it comes to government action. There is much scope for further investigation of interactions of expert surveys and industry / cluster level analysis.

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