GOVERNING VALUE CHAIN DISRUPTION IN AGRICULTURE AND AGRI-FOOD PRODUCTION: A BEHAVIOURAL APPROACH TO ASSESSING MARKETS FOR AGRICULTURAL DATA

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ABSTRACT

Many experts predict that the global economy is headed toward a future wherein 'data is the new oil.' The agriculture and agri-food sector is no exception, considering that agricultural data—data generated to improve primary agricultural production—holds a great deal of valuable information about the global food supply, present and future. As digital hardware and software rapidly introgress agricultural production systems, an on-farm transformation in productivity and efficiency is creating the conditions for an impending value chain transformation driven by ag-data. Though still on the horizon, policymakers should pay close attention to how this future unfolds and consider the oncoming role of policy in promoting the ideal conditions for growth, innovation, and mutual benefit among stakeholders.

Policymakers must strive to understand more about a variety of questions, including what disruptive 'secondary uses' of ag-data will be, who stands to win or lose, how much ag-data is worth, who will own it, and what ownership entails. One key issue is the rules and conditions under which ag-data will be exchanged. This thesis advances a behavioural approach to understanding the dynamics underlying an emerging market for ag-data, especially assessing whether the initial assignment of ownership affects the valuation and end-distribution of benefits—i.e. whether there is an endowment effect present in the exchange of ag-data. A secondary analysis considered the impact of subjects' worldviews within the same transactional environment. A cohort of agriculture students at the University of Saskatchewan (USask) were surveyed as a proxy for agricultural producers. The results indicate a strong endowment effect, suggesting the initial allocation of property rights over ag-data may strongly influence their end-distribution in a transactional market. This finding suggests that policy intervention may be in the public interest.

Keywords: Digital agriculture; data; ownership; endowment effect; data markets

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LIST OF ABBREVIATIONS

Ag Data Transparency Evaluator (ADTE)

Agricultural Data Coalition (ADC)

Agricultural Technology Provider (ATP)

Farm Credit Canada (FCC)

Global Open Data for Agriculture and Nutrition (GODAN)

Gross Domestic Product (GDP)

International Political Economy (IPE)

Internet of Things (IoT)

Unmanned Aerial Vehicle (UAV)

University of Saskatchewan (USask)

Variable Rate Technology (VRT)

CHAPTER I. INTRODUCTION

1.1 OVERVIEW

Many experts predict that the global economy is headed toward a future wherein 'data is the new oil.[1] The agriculture and agri-food sector is no exception, considering that agricultural data ("ag-data")—data generated to improve primary agricultural production—hold much valuable information about the current and future global food supply.[2] As digital hardware and software rapidly introgress agricultural production systems, an *on-farm* transformation in productivity and *efficiency* is creating the conditions for an impending value chain transformation driven by ag-data. This transformation will occur as ag-data emanate from *on-farm* and permeate the broader agriculture and agri-food value chain to find new use-cases that generate new economic value.[3] While the *on-farm* transformation benefits both producers and agribusinesses, the broader value chain transformation may deliver zero-sum outcomes whereby value migrates from producers to large agribusinesses.[4] Though still on the horizon, policymakers should pay close attention to how this future unfolds and consider the role of policy in shaping the ideal conditions for economic growth, innovation, and mutual benefit among stakeholders.[5]

Today, the definite forms this value chain disruption will take and the stages of its unfolding remain unclear. Nevertheless, policymakers must confront these possibilities and strive to understand more about *two* overarching sets of questions. The first set concerns *technology*: how will various stakeholders leverage ag-data *off-farm* (i.e. new use-cases) and to what consequences (i.e. who wins and loses)? The second set concerns *institutions*: how can policy create institutions that maximize the benefits and minimize the detriments of ag-data use across the agriculture and agri-food value chain? Developing better answers to each set of questions will empower policymakers to shape the conditions needed to better steer this digital transformation toward the public interest. This thesis confronts this challenge via a behavioural approach to modeling the outcomes of a transactional market for ag-data.

1.2 THE POLICY PROBLEM

The focus of most scholarship on the digitization of agriculture and agri-food production has been limited to *on-farm* economic activity; thus, the implications of ag-data permeating the broader agri-food value chain (i.e. the *off-farm* transformation) remain underexplored. This is largely because most current ag-data use-

1 "The World's Most Valuable Resource Is No Longer Oil, but Data."
2 Wolfert et al., "Big Data in Smart Farming – A Review."
3 Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."
4 Johnson, "Precision Agriculture."
5 Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."

cases consist in activities related to primary agricultural production (i.e. *on-farm* use-cases). However, as the global economy enters the Fourth Industrial Revolution and data become more portable and applicable to new use-cases, the impact of ag-data is unlikely to remain confined to *on-farm* economic activity—in fact, evidence suggests that the early stages of *off-farm* disruption are already underway, albeit in only a few discrete places so far. Studying these developments is challenging in that potential *off-farm* use-cases for ag-data are *technologically* underdeveloped (or, potentially, hidden to avoid regulatory scrutiny) while, *institutionally*, little structure exists to shape flows or adjudicate control of ag-data and its (current or future) use-cases. Such analytical challenges are inherent to the study of emerging technologies.

This thesis confronts these challenges. Without formal property rights in ag-data, *de facto* ownership (arising from advantages in technology, capital, and knowledge) has defaulted to the agribusinesses currently collecting, storing and controlling ag-data. As these agribusiness giants reposition for the future and develop strategies to leverage ag-data,[6] policymakers must consider whether the status quo best serves the public interest and, if not, how formalizing property rights in ag-data might positively shape markets for ag-data such that agribusinesses and producers could participate in ways that would optimize the diffusion of this transformative technology.

The narrower question is whether such markets would allocate property rights in ag-data in ways that deliver *efficient* economic outcomes. Classical economics contends that, provided the minimal conditions for a free market, rational actors will bargain toward *efficient* outcomes, with the initial allocation of property rights impacting *equity* but not *efficiency*.[7] However, a considerable body of evidence from the behavioural economics literature contends otherwise—namely that individuals (in this case, agricultural producers) rarely behave strictly rationally, often making decisions that undermine the *efficiency* of Coasian bargaining. This thesis examines the behavioural dynamics underlying a prospective market for ag-data, asking specifically whether initial endowment impacts the *efficiency* of distribution and—by extension—the value generated through its resulting use-cases.

In the broader *value chain transformation* of agriculture and agri-food production, ag-data has the potential to generate tremendous value both *on-farm* and, increasingly, through a plethora of *off-farm* use-cases. Answering behavioural questions regarding transactions should help policymakers decide whether (and how) intervention could shape effective ag-data markets. The correct institutional configuration would remain conducive to innovation and *efficiency*, promote greater trust and predictability, and allocate property rights such that ag-data drives positive-sum outcomes that benefit all stakeholders.[8]

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6 Lowy, "Monsanto Is Bridging Genetics and Big Data Analytics"; Kanaracus, "Monsanto Bets Nearly $1 Billion on Big Data Analytics"; Manning, "What Is Ag Big Data? How 8 Companies Are Approaching It"; Roumeliotis and Burger, "Bayer Clinches Monsanto with Improved $66 Billion Bid."

7 Coase, "The Problem of Social Cost."

8 Schrimpf, "Farmobile Addresses Data Transparency With New Legal Agreement."

1.3 POLICY OBJECTIVES & THE PUBLIC INTEREST: A TALE OF TWO FUTURES

Disruption is the corollary of innovation in that technological change always produces winners and losers. Governing the digitization of food and emerging use-cases for ag-data will require institutions (both regulatory and proprietary) to align innovation with the public interest (i.e. maximize positive and limit adverse impacts). Where, inevitably, there are losers, policy must provide compensation to ensure a minimum acceptable degree of loss.[9] The 'public interest' is a broad and subjective concept that balances considerations of growth vs. sustainability, innovation vs. competition, value creation vs. migration, economy vs. society, and *efficiency* vs. *equity*. Further, these sets of goals rarely present direct trade-offs, especially in the longer-term. In the context of Canadian agriculture and agri-food production, the primary goals are domestic food security, economic and export growth, innovation, and environmental sustainability—all of which are critical and highly interrelated. However, this thesis focusses more narrowly on balancing the goals of economic *efficiency* and *equity* (while aligning innovation with these goals).

When considering the eventual outcomes of innovation, it is helpful to imagine the end-point of several potential paths taken to their logical extremes. To that end, the digitization of agriculture and agri-food production could result in one of two hypothetical futures, one dystopian and the other utopian. The US chicken industry provides a cautionary tale for how monopoly and the centralization of control over data has concentrated the benefits of production and innovation in the hands of the oligopolistic firms that dominate the sector.[10] Though this thesis is concerned exclusively with crop agriculture, the case of US poultry is relevant in that the two share several similarities. Parts of the crop agriculture value chain are similarly dominated (though to a lesser degree) by massive, vertically-integrated players such as DowDuPont, Syngenta AG, and Bayer (which acquired Monsanto in 2016[11]) in biotech (seeds) and agrichemicals; Deere & Co. and CNH Industrial NV in farm equipment; and Cargill, Bunge, and Archer Daniel Midland in crop commodity trading and processing. The other vexing similarity is the precarious position of many producers, owing largely to environmental risk (e.g. drought and flooding amid increasing climate volatility) and economic uncertainty (e.g. unstable input and commodity prices) that threaten already-thin profit margins.

This thesis explores the justifiable concern that the increasingly centralized control (i.e. de facto ownership) over growing volumes of ag-data could enable monopolistic rent-seeking by agribusinesses that would further exacerbate producer vulnerability and result in economic marginalization similar to that observed in the US poultry industry. However, to the extent that *off-farm* use-cases for ag-data have yet to emerge, the current moment presents an ideal opportunity for proactive policy intervention. Before new norms become

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[9] Trebilcock, *Dealing with Losers*.
[10] Leonard, *The Meat Racket*.
[11] Hube, "Bayer's Deal for Monsanto Looked Like a Winner. Now It Looks Like a Lesson in How Not to Do M&A."

entrenched, policymakers have an opportunity to influence the conditions for inclusive growth and innovation. Despite signs portending a dystopian future, this thesis explores how *institutions* could, instead, steer the digitization of agriculture and agri-food toward one that looks considerably more utopian. Agriculture has long served as the base of many economies and formed the bedrock of communities, societies, and nations. In 1787, Thomas Jefferson wrote, "Agriculture is our wisest pursuit, because it will in the end contribute most to real wealth, good morals and happiness."[12] This vision still holds true today, but will now depend—perhaps more than ever, amid a digitizing global economy—on sound, enlightened, and timely policymaking.

[12] Jefferson and Washington, *The Writings of Thomas Jefferson*.

CHAPTER II. THE DIGITIZATION OF AGRICULTURE AND AGRI-FOOD PRODUCTION

2.1 OVERVIEW

Most discourse on the digitization of agriculture and agri-food production has focussed on *on-farm* advancements in efficiency and productivity (i.e. precision agriculture), often evoking high-minded ambitions like the United Nations' Food and Agriculture Organization's goal to increase food production by 60% to feed a projected 9-10 billion people by 2050.[13] However, the truth is that this transformation has as much to do with profit motives as the food security goals championed in international development slogans. As the global economy enters the Fourth Industrial Revolution, no sector will remain untouched by the sweeping disruptions enabled by mass data generation, increased computational capacities, and the further integration of mechanical, digital, and biological systems.[14] In today's global economy, firms that most effectively use and control data reign, so much so that seven of today's ten highest-valued global companies are data-driven technology firms.[15] There can be little doubt that agribusiness leaders are now acutely focused on their own opportunities to capitalize on the vast quantities of ag-data generated *on-farm* by their technologies. As the latest digital technologies introgress the agriculture and agri-food value chain, closer examination reveals that there is more than feeding the world at play. This section provides a descriptive background of this transformation.

2.2 ECONOMIC INDICATORS

In 2017, the global agriculture and agri-food sector (including related supply and service activities) contributed USD$3.2 trillion to global gross domestic product (GDP) (3.8% of total)[16] and employed approximately 1.3 billion people (roughly one third of the global workforce).[17] Agriculture and agri-food production is a particularly important sector in Canada's economy and Canada is a major player in the global agriculture and agri-food value chain. In 2016, the sector contributed $111.9 billion to total Canadian GDP (6.7% of total) and employed roughly 2.3 million people (12.5% of Canadian employment).[18] Between 2012 and 2016, GDP growth in the sector (11%) outpaced that of the broader Canadian economy (7.8%).[19] In 2017, Canada recorded $110 billion in domestic agriculture and food processing sales.[20] In primary agriculture, 2016

[13] Food and Agriculture Organization of the United Nations, "Feeding Nine Billion in 2050."
[14] Schwab, "The Fourth Industrial Revolution."
[15] "How to Think about Data in 2019."
[16] World Bank, "GDP (Current US$) | Data."
[17] UNCTAD, "Investment Policy Hub."
[18] Agriculture and Agri-Food Canada, "An Overview of the Canadian Agriculture and Agri-Food System 2017."
[19] Agriculture and Agri-Food Canada.
[20] "Canada's Economic Strategy Tables: Agri-Food."

saw farm market receipts reach a record high of $57.6 billion, the result of a 5.8% average yearly rate of growth between 1971 and 2016.[21] Moreover, in 2017, Canada exported $56 billion in agriculture and agri-food products,[22] and, as of 2016, Canada is the 5th largest global exporter of agricultural commodities ($24.6 billion; 5.3% of global agricultural commodity exports); since 2014, Canada has been consistently the 11th largest global exporter of agricultural and agri-food products.[23]

2.3 AGRICULTURE IN THE FOURTH INDUSTRIAL REVOLUTION

2.3.1 A Chain of Technological Revolutions

It is critical to situate the digitization of agriculture and agri-food production in the context of the broader Fourth Industrial Revolution, a defining feature of which is the digitization of all economic sectors. Whereas previous waves of agricultural innovation were limited mainly to mechanical and biological innovations, ag-data are now digitizing (i.e. digitally capturing and elucidating) vital processes and outcomes in primary agriculture and introgressing both mechanical (IoT) and biological (CRISPR, 'the digital plant,' etc.) technologies in the value chain. This deeper integration of mechanical, digital, and biological systems is a defining feature of the Fourth Industrial Revolution.[24]

This transformation is not occurring in a vacuum or through some exogenous set of developments; rather, the sector arrived at this point by a long chain of prior, interrelated technological and institutional transformations. Agricultural innovation has long held a central position in the global economy, advanced the welfare of society, and propelled the broader trajectory of innovation throughout economic history—directly and indirectly contributing to transformations far beyond the fields in which crops and animals are cultivated. This is largely because agriculture and food serve as base for all economies and societies. So sensitive is the global order to international flows of agricultural commodities, ingredients, and food products that even a short interruption in their production and trade would halt large segments of global economic activity and destabilize social order in many countries. Technological leaps in agriculture have worked to propel humanity forward, the earliest example being the development of crop cultivation in ancient Mesopotamia, considered by many to be the dawn of civilization.[25] Long after, between 1500 and 1850 CE, the Second Agricultural Revolution (also known as the British Agricultural Revolution), involving techniques such as crop rotation, vastly increased land and labour productivity, emancipating much of Britain's workforce from meagre agricultural subsistence. This

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[21] Agriculture and Agri-Food Canada, "An Overview of the Canadian Agriculture and Agri-Food System 2017."
[22] Agriculture and Agri-Food Canada.
[23] "FCC Ag Economics Trade Ranking Report: Agriculture."
[24] Schwab, "The Fourth Industrial Revolution."
[25] *Ancient Mesopotamia at the Dawn of Civilization.*

transformation freed up labour for other activities, a shift that was a necessary to the First Industrial Revolution and, by extension, all those that followed.[26]

Similarly, the Third Agricultural Revolution of the 1950s and 1960s enabled the productivity increases needed to supply enough food for the global population to reach today's levels[27] (currently above 7.5 billion[28]). Today, we are challenged to feed a projected 9-10 billion people by 2050;[29] achieving this will require increasing global food production by between 60-100%, even as climate change reduces the supply of arable land and fresh water available for crop cultivation. Success will depend, in part, on fully leveraging ag-data across the broad agriculture and agri-food supply chain (i.e. the *value chain transformation*).[30] While further digitization offers many of the best solutions to a complex array of challenges, this thesis explores how it also presents its own set of risks and, thus, opportunity for policy intervention.

2.3.2 From the Third to the Fourth Industrial Revolution

The Third Industrial Revolution, beginning post-WWII, began a process of accelerated global digitization, escalating with the semiconductor revolution of the 1960s, followed by the personal computer in the 1970s, the development of digital networks in the 1980s, the rise of the contemporary internet (e.g. e-commerce, search, and social media) in the 1990s and 2000s, and mobile and cloud computing in the last decade.[31] Much as steam defined the First Industrial Revolution, data and information have come to define the Third and Fourth Industrial Revolutions.

However, what sets the Fourth revolution apart is a paradigm shift regarding data. Schonberger and Cukier hailed this shift in their seminal book entitled *Big Data* (published in 2014), which foretold this new technology "migrating to all areas of the human endeavor." The authors pointed out that, just five years before the book's release, 'big data'—defined simply as "the ability of society to harness information in novel ways to produce useful insights or goods and services of significant value"—did not exist, nor could it have.[32] In part, this is because providing the degree of computing power and storage necessary to analyse massive datasets had been infeasible (either technically or financially). However, the most critical ingredient was the shift in paradigm whereby raw data ceased to be "regarded as stale or static" to re-emerge as "a raw material of business [and] a vital economic input, used to create a new form of economic value."[33]

[26] Overton, "BBC - History - British History in Depth."
[27] Hazell, *The Asian Green Revolution*.
[28] United States Census Bureau, "U.S. and World Population Clock."
[29] Silva, "Feeding the World in 2050 and beyond – Part 1."
[30] An et al., "Chapter 25 - Agriculture Cyber-Physical Systems."
[31] "Welcome To The Unicorn Club."
[32] Mayer-Schönberger and Cukier, *Big Data*.
[33] Mayer-Schönberger and Cukier.

This new omnipresence of data extends the scope of tasks computers perform to a degree beyond what many, even recently, imagined possible.[34] Each day, increasingly sophisticated algorithms transform the world of information and automate more and more cognitive processes (and at ever-greater speeds, thanks to Moore's Law[35]), while robotics increasingly automate processes in the physical world. Today's most-subscribed digital platforms (e.g. social media and search engines) track users online activities to extract value from understanding their behaviour; in these cases, data capture the 'who, when, where, why, and how' of people living their lives—or, as a recent Economist article put it: "Data is us."[36] However, increasingly, sensors also capture non-human operations in the physical economy, 'datafying' the core processes and outcomes of virtually all economic activity, including resource extraction and crop cultivation, design and manufacturing, transportation and storage, trade, as well as all online commercial activity.[37] As they are aggregated into massive, diverse, and dynamically expanding datasets, these data are rapidly finding new applications, especially as analytics tools and techniques improve and firms integrate real-time data into existing industrial systems and decision-making processes.[38] Moreover, increasing interoperability (i.e. data integration through APIs) will further extend the applicability of datasets to new use-cases.

The view that "data is the new oil" garners consensus as many of today's firms invest intensively in their capacity to collect, store, analyze, and leverage massive datasets.[39] As more firms compete to adopt, integrate, and develop new hardware and software, and to automate and digitize a wider range of core business processes, the competitive goalposts are continually moving—particularly amid continuing forces of globalization.[40] Critically, digitization is driving massive economic growth: The World Economic Forum estimated that in 2014, the digital economy contributed $2.8 trillion to global GDP and claimed that "cross-border dataflows now generate more economic value than traditional flows of traded goods."[41] McKinsey Global Institute estimated that by 2025, this increased cyber-physical integration of economic systems will generate over US$125 trillion in gross value[42] (for perspective, the World Bank estimated Gross World Product in 2016 at $76 trillion);[43] AgFunder reports that agtech investment activity globally accelerated dramatically between 2012 and 2018, totalling US$ 55.5 B over the period and US$16.9 B in 2018 alone.[44]

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34 Manyika et al., "A Future That Works: Automation, Employment, and Productivity."
35 Moore, "Cramming More Components onto Integrated Circuits."
36 "How to Think about Data in 2019."
37 "7 Industries That Will Be Radically Changed by the IoT"; Cukier and Mayer-Schoenberger, "The Rise of Big Data."
38 Chen, Chiang, and Storey, "Business Intelligence and Analytics: From Big Data to Big Impact."
39 "The World's Most Valuable Resource Is No Longer Oil, but Data."
40 Bersin, "Everything Is Becoming Digital."
41 Baller, Dutta, and Lanvin, *The Global Information Technology Report 2016*.
42 Manyika et al., "Disruptive Technologies: Advances That Will Transform Life, Business, and the Global Economy."
43 World Bank, "GDP (Current US$) | Data."
44 Fulton, Port, and Colley, "The Data Ownership Confusion."

2.4 PRECISION AGRICULTURE (THE *ON-FARM* TRANSFORMATION)

Amid this process of mass digitization, many observers have overlooked innovations in agriculture and agri-food production, despite its long history at the forefront of technology adoption (recently and most visibly, autonomous vehicles[45]). Advances in digital technology over the last decade have revolutionized primary production[46] and most digital innovation in agriculture has, so far, occurred *on*-farm. Even as ag-data permeate the broader value chain, the locus of digitization will remain *on-farm* in that ag-data originate *on-farm*, digitally capture *on-farm* processes and outcomes, and enable *on-farm* use-cases that improve primary (i.e. *on-farm*) agricultural production.

The Green Revolution of the 1960s[47] was followed by vast improvements to machinery and the implementation of superior management practices.[48] Meanwhile, much of Asia, Africa and Latin American remain, to this day, largely "untouched by modern technology."[49] The hallmark of 'precision agriculture' is the digitization of primary production towards a future of increased automation and precision (i.e. more efficient utilization and placement of inputs), which is expected to both contribute to feeding the growing global population and help sustainably manage resources amid a warming global climate; agriculture currently uses roughly "55% of non-forest land, 80% of total freshwater, and 30% of fossil fuels" consumed globally each year.[50]

2.4.1 GPS/GIS Guidance

The earliest developments in precision agriculture date back to the 1980s with the application of global positioning system (GPS) and global information system (GIS) technology to farm machinery (i.e. tractors, combines, sprayers and seeders, etc.).[51] As consistently straight field rows had long been a hallmark of quality farming, the initial objective of precision agriculture was to automate steering for greater precision. Over the past 25 years and since the advent of these innovations, mass adoption has also all but eliminated human error from steering in seeding, spraying, and harvesting processes. Autosteer also frees up producers to attend to other tasks while significantly cutting down on the wastes associated with overlap (i.e. applying seeds or other

[45] Jancer, "The Transformer of Autonomous Farmbots Can Do 100 Jobs on Its Own."
[46] Bronson and Knezevic, "Food Studies Scholars Can No Longer Ignore the Rise of Big Data"; Carolan, "Publicising Food"; Cheng and Sonka, "Big Data."
[47] American Farm Bureau, "Farmers, Agriculture Technology Providers Reach Agreement on Big Data Privacy and Security Principles Expected to Accelerate Technology Adoption."
[48] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[49] Rehman et al.
[50] Strothkämper, "A New Agricultural Revolution, Courtesy Of The Internet Of Things And Machine Learning."
[51] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."

inputs in the same area more than once).[52] Today, most producers in the developed world have adopted GPS/GIS-guidance.[53] Moving into the future, the logical extension of this technology is fully-autonomous farm machinery; in spring 2018, the launch of SeedMaster's autonomous Dot Power Platform marked the first commercial deployment of this technology in agriculture.[54]

2.4.2 Sectional Control

Concurrent with this trend toward greater automation, a technology called *sectional control* (also called 'swath control') represents a further degree of *precision* in ag-production. Equipping to both sprayers and seeders, sectional control leverages GPS/GIS to automatically disable individual seeder rows or sprayer nozzles when a vehicle runs outside a set boundary or passes over land that has already been seeded, fertilized, or sprayed.[55] This capability is particularly useful when dealing with irregularly shaped areas and when navigating headlands (i.e. the parameters of a planted field). Sectional control presents a clear value proposition that focusses on saving producers a great deal in costs for seed, fertilizer, pesticides, and herbicides, while also maximizing the impact of these inputs.[56]

2.4.3 Sensors

While GPS/GIS technology is the foundation of precision agriculture, it is the recent decision of ag-manufacturers to embed sensors in nearly every newly-manufactured tractor, combine, sprayer and seeder that has truly set the stage for an *on-farm* and (particularly) *off-farm value chain* transformation driven by ag-data.[57] This shift was enabled by recent reductions in the cost of sensors as well as ID-related advancements in computing.[58] However, the sudden ubiquity of sensors in ag-machinery is likely also a testament to the (speculative) *off-farm* value of ag-data, which contains valuable information (i.e. soil, climate, seed, input and application decisions, and yield) that could help predict the quantities and qualities of the future global food supply across various geographies.[59]

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[52] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[53] Rehman et al.
[54] Jancer, "The Transformer of Autonomous Farmbots Can Do 100 Jobs on Its Own."
[55] Sonka and Cheng, "A Big Data Revolution: Who Would Drive It?"
[56] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[57] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."
[58] Suprem, Mahalik, and Kim, "A Review on Application of Technology Systems, Standards and Interfaces for Agriculture and Food Sector."
[59] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."

This flood of sensors into new ag-equipment has also come in the form of unmanned aerial vehicles (UAVs),[60] which collect infrared, multispectral, or thermal infrared images that are digitally rendered to produce actionable assessments of crop health, elevation, and input distribution.[61] Farm management software analyzes, reorganizes, and stylizes these data to provide "accurate 2D orthomosaic [and] 3D models" from which producers can empirically assess how parameter adjustments may have led to positive or negative outcomes.[62] Today's vast array of sensor-based technologies, often used in concert, represent a further degree of intensification in precision agriculture, but also—just as importantly—the entrance of agriculture into the so-called data economy through the generation of ag-data.

2.4.4 Variable Rate Technology (VRT)

Though "farming has been empirically driven for over a century,"[63] a new degree of data-driven precision is bringing the science of agronomy closer than ever to the praxis of daily farming. Theoretically, sufficient ag-data are now available to augment decision-making to the extent that 'satisficing' need not remain the *modus operandi* for most decision-making processes in ag-production processes. However, in practice, many challenges remain. So far, these data and the processes whereby they are used appear to be a compliment rather than substitute for human-decision making, empowering producers to make better-informed decisions, in real time, based on statistically-significant datasets.

Finally, variable-rate technology (VRT) represents yet a further degree of intensification in precision agriculture. VRT translates ag-data into digital prescriptions that control seed metering and spraying rates to match input application in real time to the agronomic needs of unique field locations. Based on geographical location, VRT-enabled equipment varies input application rates by shutting on and off individual components as necessary.[64] Application prescriptions are ultimately determined by the agronomic information corresponding to precise locations, including soil health, elevation, and NDVI maps of vegetative health.[65] VRT also enables seeders and sprayers to navigate more challenging topographies by varying application rates to match elevation-based growth capacity.[66]

Today, VRT adoption remains slow due mainly to the high costs and the steep learning curve associated with the technology. For many, the cumulative fixed cost for a wide array of complementary precision ag technologies is prohibitive, especially considering a range of persistent risks (e.g. weather, pests,

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60 Burwood-Taylor, Tilney, and Chauhan, "AgTech Investing Report: Mid-Year 2016."
61 Green Aero Tech, *Aerial Imaging Services for Agriculture*.
62 Green Aero Tech, *The Complete Solution for Aerial Mapping*.
63 Bronson and Knezevic, "Big Data in Food and Agriculture." 1.
64 Suprem, Mahalik, and Kim, "A Review on Application of Technology Systems, Standards and Interfaces for Agriculture and Food Sector."
65 Mondal and Tweari, "Present Status of Precision Farming."
66 Norac, TopCon Positioning Group, *Boom Height Control*.

disease) that threaten to undermine these investments. Many producers also face financial constraints and tightening margins as competitors pursue greater economies of scale by adding acres to their operation.[67] This drive to consolidation has pushed many small- and medium-sized producers out of the market and left many of the rest tenuously holding on (one expert opined that the minimum viable size for a Canadian farming operation is approaching 3000-4000 acres[68]). Despite this financial drag on adoption among small- and medium-sized producers,[69] experts predict an uptick in VRT adoption as early adopters work out kinks in the technology and realize significant returns on investment, thereby validating the technology for later adaptors. As this thesis will explore, the role of policy in increasing producers' trust through clarifying ag-data ownership will likely be critical to driving greater adoption of precision agriculture technologies.[70]

2.4.5 Smartphones (Internet of Things)

Last, the smartphone has become increasingly central to precision agriculture systems.[71] Sensors have enabled agribusinesses to offer many new hardware devices that, among other functions, monitor key production parameters (e.g. the volume, heat and moisture of stored commodities; irrigation cycles). Smartphones serve as a universal remote-control device to monitor and operate a range of agricultural productions systems.[72] The network of interconnected digital devices that continually collect, process, and transmit this data exemplifies the 'Internet of Things'— defined as a network of devices that are physically distributed but digitally interconnected.[73]

All the aforementioned technologies embody the 'precision agriculture' concept. This brief overview barely scratched the surface of a bounty of innovations introduced to overcome current issues in ag-production. These new digitally-driven *on-farm* processes generate tremendous volumes of ag-data, in turn, creating the potential for a broader *value chain* transformation. Though the *on-farm* transformation is locus of digital transformation, the eventual impact of ag-data permeating the broader supply chain may far exceed that of precision agriculture as ag-data migrates to food processing facilities, financial institutions, R&D projects, blockchains, and anywhere else new value could potentially be realized.

[67] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[68] VanCaeseele, Interview with Chris VanCaeseele, CropPro Consulting.
[69] Sullivan, Interview with Bryan Sullivan, Farmer.
[70] McIntosh, "The Legal Mess of Farm Data Ownership."
[71] Tene and Polonetsky, "Privacy in the Age of Big Data."
[72] Aubert, Schroeder, and Grimaudo, "IT as Enabler of Sustainable Farming."
[73] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."

CHAPTER III. AG-DATA AND THE "VALUE CHAIN TRANSFORMATION"

3.1 THE "VALUE CHAIN TRANSFORMATION" OF AGRICULTURE AND AGRI-FOOD

3.1.1 The Value Proposition for Agribusiness

As precision agriculture moves toward widespread adoption, agribusinesses stand to profit considerably from establishing a new catalogue of data-driven products and services that further automate and improve the efficiency of agricultural production. However, this thesis focusses on how the *on-farm* transformation (i.e. precision agriculture) is creating the conditions for a broader *value chain transformation* driven by ag-data. The ongoing digital transformation of all major sectors, including business, finance, and healthcare,[74] has fixed the gaze of leaders in every industry on the 'big data future'—i.e. the untapped value of insights from analysing troves of diverse, aggregated data.[75] Though they have yet to fully implement strategies to leverage ag-data, leaders in agribusiness are betting on the same future.

Each day, several thousand farms across the developed world collect vast quantities of data that capture yield, moisture, climate, soil and input application, and many other features in ag-production.[76] This highly valuable information could answer several important commercial questions, including how current commodity and product supplies could better meet the demands of consumers at various locations, the quality of nutrition available to billions of people, and the value (i.e. price) of commodities, ingredients, and food at various stages of their manufacture and trade. Leveraging ag-data to more effectively answer these (and other) questions presents a massive opportunity for agribusinesses to capture new and existing value. Though it is too early to tell, profits from *off-farm* use-cases for ag-data could eventually outstrip those from selling precision agriculture products.

Many experts acknowledge that that "to date only a small portion of [ag-data] is being used and shared with partners such as advisors, suppliers, buyers, consumers and government."[77] Nevertheless, many also foresee that, as technologies progress and volumes of ag-data expand,[78] so too will opportunities to commodify and leverage it. Many forms of data already play "the role of an oracle providing insight on seasonal activities…informing insurance policies, finance facilities, and commodity exchanges,"[79] so integrating ag-data

[74] Henke et al., "The Age of Analytics: Competing in a Data-Driven World."
[75] Chen, Chiang, and Storey, "Business Intelligence and Analytics: From Big Data to Big Impact."
[76] Harris, "Building a More Efficient Road Map for Agricultural Data."
[77] "2018, Year of Data in Agriculture."
[78] Archer and Delgadillo, "Key Data Ownership, Privacy and Protection Issues and Strategies for the International Precision Agriculture Industry."
[79] Byrum, "Data As Agriculture's New Currency."

appears an intuitive proposition. Precision agriculture provider Farmobile claims, "We have data buyers calling us like crazy…[f]rom reinsurance companies to technology giants to chemical and seed companies," all "hungry for a consistent stream of high-quality, layered, ground-truth farm data."[80] Perhaps the best illustration of the ag-data opportunity came from agricultural lawyer (and ag-data thought leader) Todd Janzen in his November 2017 testimony to the US Senate's Subcommittee on Consumer Protection, Product Safety, Insurance and Data Security:

> *"This marks the first time in history that the majority of the information that farmers generate and use on their farms has been moved into the hands of companies outside the farm. As a result, we are seeing a digital land-rush occurring across the United States. The past few years have seen millions of dollars pour into ag data startups from Silicon Valley, to Kansas City, to North Carolina. Historic legacy agricultural companies, such as John Deere, are also at the forefront of this movement by expanding their product offerings to include cloud-based data storage platforms. All of these companies are scrambling to get the most acres of data into their platforms so that when consolidation of ag technology providers (ATPs) begins, they are in the strongest position. In the race to the cloud, we must also be cautious so that the American farmer is not left behind."*[81]

3.1.2 What Does 'Big Data' Look Like in Agriculture and Agri-Food Production?

As more commentators discuss the 'big data' revolution in agriculture, the term bears closer examination. Ellixson and Griffin define big data in this context as "aggregated farm data gathered from numerous farming operations into a single database or repository," effectively "combining each farmer's data across a geographic region."[82] The notion of 'big data' can be nebulous in that scale is its defining feature: the label applies only where a certain volume threshold is satisfied, whereupon a "change in scale" (i.e. a quantitative change) begets a "change in state" (i.e. a qualitative change).[83]

Not all *on-farm* use-cases for ag-data satisfy this threshold. For example, in precision agriculture, sensors embedded in machinery and UAVs *on a farm* may collect data only about the conditions *of that farm* to harness precision agriculture capabilities that intensify productive capacity *of that farm*. Leveraging individualized ag-data may not meet the 'big data' threshold in that few individual farms are 'big' enough to solely generate sufficient volumes of data.[84] The term is more appropriate to *on-farm* use-cases involving aggregated datasets generated across many farms (e.g. for benchmarking or universal prescriptions). Similarly, not all potential *off-farm* use-cases entail aggregating ag-data at the regional, national or international level; however, those that do may come to embody the connotations of *big data* to the greatest extend yet.

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[80] Begemann, "DataStore Means Farmers Can Sell Data For Real Dollars."
[81] Janzen, "US Senate Testimony."
[82] Ellixson and Griffin, "Farm Data."
[83] Mayer-Schönberger and Cukier, *Big Data*.
[84] Manning, "What Is Ag Big Data? How 8 Companies Are Approaching It."

The functions of big data are highly intertwined with other digital technologies considered vis-à-vis ag-data, such as artificial intelligence and machine learning, cloud computing, IoT, and, in some cases, blockchain. In fact, the promise of big data may hinge on integrating these other technologies, as evidenced in John Deere's acquisition of Blue River Technologies, an event many considered a harbinger for "machine learning and artificial intelligence" moving "from a concept to real [use-cases] on the farm."[85]

As agribusinesses, through various network and partnership, aggregate and successfully leverage more and more ag-data, so grows the need for policy to shape these data flows and—most importantly—to define who controls and benefits from them. In the open data literature, de Beer notes that "formal legal frameworks become most important…when open data initiatives are scaled up" in that "scalability is the fulcrum on which the balance between formal and informal governance of open data pivots," whereupon "clear legal rules then become integral to delineate the scope of data ownership and promotion of openness."[86]

3.1.3 The Agriculture and Agri-Food Value Chain and Technologies

Visualizing the agriculture and agri-food value chain is helpful in considering *off-farm* use-cases and their implications. Figure 1 provides a basic outline of this value chain.

Upstream (off-farm)	***On-farm***	**Downstream (*off-farm*)**				**Distribution & Retail**
		Handling & Commodities Markets	Processing (ingredients)	Food Mfg.	Transportation & Trade	
Biotech **Agrichemical** **Equipment (and ATPs)**	Agricultural production • Seeding • Feeding • Harvesting	Grain elevators Financial inst.	Processors • Mills • Fractionation			Grocery stores

Figure 3.1: Agriculture and Agri-Food Value Chain

'Upstream' refers to the agribusinesses that provide the (non-land) inputs to primary agricultural production:

- Conventional and biotechnology companies (i.e. seeds and genetics);
- agrichemicals (i.e. fertilizer, herbicides, pesticides, and fungicides); and
- agricultural equipment providers (i.e. machinery, hardware, and software).

Critical 'downstream' actors include agricultural:

- commodity handlers, who receive, purchase, and transport raw agricultural commodities;
- processors of ingredients and food products;
- actors involved in the transport and trade of food products for final retail and distribution; and

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[85] Janzen, "Ag Tech Predictions for 2018."
[86] de Beer, "Ownership of Open Data: Governance Options for Agriculture and Nutrition."

- food and beverage retailers, who distribute final food and beverage products to consumers.

Currently, upstream actors (i.e. biotechnology, agrichemical, and equipment) comprise the majority of agricultural technology providers (ATPs) supplying the precision agriculture products producers use generate and leverage ag-data *on-farm*. As a result, in the early stages of the 'digital land-rush,' upstream players are in the best position to control ag-data flows and have the largest stake in developing new use-cases. As with precision agriculture, many new use-cases could drive positive-sum growth and benefit producers and ATPs alike (often called value creation); alternatively, some new *value chain* applications for ag-data could drive zero-sum outcomes by enabling agribusinesses to capture value at the expense of producers (sometimes called value migration). Interestingly, many of the potential risks to producers lie in downstream use-cases, particularly those concerning commodity markets. This raises questions about if and where upstream ATPs (who currently control ag-data flows) see opportunity in downstream ag-data use—whether they are targeting their efforts on expanding their operations downstream or by selling ag-data to established downstream players (e.g. commodity handlers or commodity futures traders).

In any case, as ag-data migrates downstream—whether via an open or transactional model—incumbents in these spaces will likely join the 'digital land-rush,' striving to grow their presence and vie for more control over ag-data flows. Policymakers should closely track the development of *off-farm* use-cases with a view to the forming institutions to structure increasingly complex, multilateral data flows between agribusinesses across the value chain. This is the developing context this thesis examines.

3.2 AG-DATA USE-CASES: PRIMARY, SECONDARY & TERTIARY USE

While all development in the *value chain transformation* remains ostensibly nascent, early signals point to several potential use-cases. These cases vary both in where they reside in the value chain (i.e. upstream or downstream) and their potential impact on agricultural producers (i.e. positive, negative, or neutral).

By definition, the inherent purpose of agribusiness has been to provide the products and services producers need to maximize productivity and efficiency in in primary production. Consistent with this logic is the individualized, *on-farm* use of ag-data by producers toward positive-sum outcomes whereby producers and agribusinesses each benefit. The term *primary use* refers to all positive-sum use-cases that benefit both agribusinesses and producers (whether *on-* or *off-farm*). Though precision agriculture is the central *primary* use-case for ag-data, there may be several positive-sum *off-farm* use-cases relating to activities such as targeted marketing of agricultural inputs, product innovation, supply chain and logistics management, risk mitigation, and improved traceability in commodities. All are ostensibly net-positive for producers, even if agribusinesses may capture the lion's share of new value added.

The need for policy intervention would be less pressing were all ag-data use-cases positive-sum; reality presents a less sanguine future. For policymakers, the most critical area for oversight may be potential use-cases that leverage ag-data toward less favourable ends such as commodity speculation, anticompetitive practices, and other activities that erode privacy, concentrate market power, deepen information asymmetry, or generally promote zero- or negative-sum outcomes—i.e. where agribusinesses profit not by creating new value but extracting value by eating at the margins of producers (i.e. rent-seeking). Therein lies the greatest potential for market failure and where the digitization of food systems risks undermining the public interest. The term *secondary use* will refer to potential zero-sum use-cases that create little or no new value, instead transferring value from producers to one or more agribusinesses. To safeguard the interests of producers and the broader public, policymakers must beware and arrest the formation of institutions that would promote *secondary use*.

Last, the term *tertiary use* will refer to positive-sum use-cases whose benefits accrue to agribusinesses but leave producers no worse off. Likely candidates include targeted marketing of inputs, supply chain and logistics management, and risk mitigation for agribusinesses. In these early days, the line between *primary* and *tertiary* cases is far from definite; given that agribusinesses and producers likely stand to benefit from many of the same *positive-sum* use-cases (if not always equally), the distinction between *primary* and *tertiary* use, then, lies in to degree to which producers share in the new value created.

While it remains unclear which use-cases will emerge, sufficient information is available to contextualize these use-cases within a broader framework. Figure 2 depicts several potential use-cases, both *on-farm* and *off-farm*, for each of the three categories.

	Primary	**Secondary**	**Tertiary**
On-farm	*Precision agriculture* • *Productivity/Efficiency* • *Sustainability*		
Off-farm	*Improved Traceability* *Increased Land Value* *Insurance* *Regulatory Compliance* *Product Innovation*	*Price Discrimination* *Anticompetitive Practices* *Commodity Speculation*	*Targeted Marketing* *Logistics* *Risk Mitigation*

Figure 3.2: Primary, Secondary & Tertiary Use-Cases

It bears noting that *impact* (i.e. distribution of benefits and risks) is the organizing principle of this analytical framework, which aims to make out the lineaments of a picture still blurred by insufficient information, transparency, and—ultimately—technological development. It is early days yet, so each potential use-case and its impacts remain somewhat uncertain; nevertheless, proactive policymaking demands attention and consideration to each. This framework helps move toward a clearer policy goal. Chapter VIII applies these categories to an economic model that will inform a policy discussion in Chapter IX.

CHAPTER IV. THE POLICY PROBLEM

4.1 OVERVIEW

Previous chapters described the early stages of digitization in agriculture and agri-food production, tracing a line from precision agriculture to the potential *off-farm* use-cases that will define its broader *value chain* transformation. Chapter III offered a model for thinking about these use-cases in terms of their likely impact on producers. This chapter examines the *institutional* status quo and considers governance options to promote positive-sum and limit negative-sum use-cases for ag-data. However, studying an economic space in flux presents a 'meta-policy problem'—that of defining a problem within an environment whose parameters remain unclear, indeterminate, impermanent, or unknown. Despite these analytical challenges, policymakers must envision, in broad strokes, a plausible trajectory for things to come. Though it is impossible to assemble a complete picture—much less a set of attending policy prescriptions—sufficient information exists to engage this puzzle toward an outcome in the public interest.

4.2 TECHNOLOGY, INSTITUTIONS, INNOVATION & DISRUPTION

Commerce exists to fulfil human needs (i.e. demand) and the study of economics concerns the allocation of the scarce resources that meet those needs (e.g. nutrition, shelter, security, energy, mobility, healthcare, information). While the human needs driving economic activity remain mostly the same, the tools and processes industries use to satisfy them are changing rapidly through digitization. Hardware, software, and data are set to play a larger role in the processes that define all sectors and industries. Economics is also concerned with technological change and its implications vis-à-vis economic objectives. Economic potential is defined within the limits set by two dynamic boundaries: *technology* and *institutions*. Technology concerns what is possible/feasible in the physical world, while institutions exist in the space of shared human consciousness, determining both what is *possible* and what is *permitted* in terms of human organization toward commercial ends. Innovation sits at the intersection of technology and institutions, occurring when institutional elements align to enable technological progress.

4.2.1 Technology

Technology is an ever-shifting line demarcating the limits of possibility in the physical world (and, thus commercial and economic spaces), the bounds of which are continuously giving way to scientific and technological progress. Ideally, new ideas, discoveries, and technologies develop (often through R&D efforts) within or diffuse into new economic spaces, commercializing in the form of new products and processes that advance the production possibilities frontier, fulfill human needs and wants hitherto unmet, create new value, solve economic, environmental, and social problems, and maximize societal utility. Technological progress occurs in successive, overlapping layers of new, fundamental technologies (i.e. diffusion), each one finding a multitude of applications and use-cases in various economic and social spaces. As technologies diffuse, use-cases divide and multiply, akin to cellular division, as industries and firms adopt superior technologies and practices and abandon inferior ones. In each economic space, unique incentives drive adoption in waves—from early- to mid- to late-adoption of a given technology. Each successive wave of diffusion is pregnant with the seeds of the next.

4.2.2 Institutions

Institutions are the second ever-shifting boundary determining the universe of possibility in economic space. Institutions can be both formal-codified (e.g. laws, public and corporate policies) and informal-conventional (e.g. societal morals, commercial structures, business models). Both formal and informal institutions define the creative tension that, at once, constrains (e.g. regulations, corporate law) and enables (e.g. property rights, intellectual property) economic activity. Thus, institutions shape both what is permitted by law (i.e. formal) and what is possible in terms of commercial organization (i.e. commercial networks), working together to structure economic activity (e.g. the production and distribution of goods and services as well as flows of information and capital). Institutions, both formal and informal, also respond (i.e. adaptation) to technological changes, which are, themselves, the result of prior institutional efforts (i.e. innovation).

4.2.3 Innovation & Disruption

Innovation exists at the intersection of technology and institutions, occurring when the necessary alignment of commercial, economic, legal, and social institutions creates the conditions to realize technological progress. Thus, technological progress hinges not only on advancing the knowledge frontier, but also on social organization to move ideas to commercialization and eventual widespread adoption, thereby changing transforming economic and social spaces while, in turn, forcing other institutions to adapt. The goal of innovation policy is to foster the conditions necessary to enable technological progress while, at the same time, ensuring that other institutions can adapt successfully, leaving society as a whole better off.

As captured in Schumpeter's notion of 'creative destruction,'[87] disruption is the corollary of innovation in that economic change inevitably produces winners and losers. Disruption entails value migrating along *industrial*, *locational*, and *sapien* dimensions, often creating the need for policy intervention, whether by imposing rules (i.e. regulation), redirecting capital (i.e. taxation and investment in public goods), or reshaping structures of control (i.e. property rights) to better align technological change with the public interest.

[87] Pfarrer and Smith, "Creative Destruction."

4.3 OVERCOMING *TECHNOLOGICAL* AND *INSTITUTIONAL* UNCERTAINTY

This theoretical underpinning helps frame a policy problem by unpacking the *value chain* transformation of agriculture and agri-food production in terms of its *technological* and *institutional* dimensions, and the interplay between innovation and adaptation. Policymakers likely have little role *technologically* in the development of new ag-data use-cases; instead, their role is in governing the *institutional* structures that determine who controls and, thus benefits from, ag-data. Therefore, the policy objective is to arrive at an institutional configuration whereby ag-data generates the most economic value, while also ensuring that benefits are distributed *equitably* (i.e. abating *secondary* use-cases while promoting *primary* and *tertiary* use-cases across the value chain).

So far, the digitization of agriculture and agri-food production has mainly involved farm equipment collecting and leveraging ag-data to improve primary production (i.e. precision agriculture). The sensor technologies that generate ag-data are now well into the mid-stages of adoption, having been widely available to producers for over a decade. Though thousands of producers continuously generate a high volume, variety, and velocity of ag-data for *primary use*, it remains unclear where, how, and to what extent ag-data are migrating to new use-cases in the broader *value chain*. It is also unclear whether, in the long term, *off-farm* use-cases stand to generate more overall value than precision agriculture. Progress in the development of *secondary* and *tertiary* use appears to be somewhat gradual, potentially due to a lack of institutional alignment (i.e. innovation) among agribusinesses. Thus, policymakers are faced with the challenge of governing not what is already possible, but rather helping to refine what will *become possible* at some indeterminate point in the future.

On the other hand, several signals indicate that agribusinesses are in the early stages of defining structures of control over ag-data flows which will largely determine who wins or loses once the latent potential is unlocked, through *secondary* and *tertiary use*, from rapidly expanding troves of ag-data. Thereafter, those in control will either themselves leverage ag-data in potentially powerful ways or sell it to other players who can. In any case, considerable effort from major agribusiness players is now underway to control the accumulation of ag-data, much as the major technology platforms of the early 2000s (e.g. Facebook, Apple, Google) then positioned themselves to control the accumulation of user data—even before they had developed the use-cases to fully exploit its value.

4.4 THE STATUS QUO: STRUCTURES OF CONTROL

In light of clear efforts by agribusinesses to control ag-data flows, policymakers must assess the status quo and determine where it serves the public interest and where intervention is necessary. Currently, too little information is available to form a clear picture of how major agribusinesses are repositioning to control ag-data flows, particularly given that the potential use-cases motivating these efforts also remain unclear (and likely underdeveloped *technologically*). However, the fact that agribusinesses are now collecting and controlling large volumes of ag-data should be enough to motivate policymakers to investigate the potential movement of ag-data between ATPs. As major agribusinesses "like John Deere and DowDuPont invest million to create data warehouses,"[88] it is critical that policymakers understand whether and to whom ag-data are being sold across the value chain well before *off-farm* use-cases emerge.

The current institutional framework lacks definition of formal legal institutions: ag-data 'ownership' remains a misnomer outside of informal contracts that apply vaguely (if at all) to the generation, storage, sharing, transacting, and use of ag-data.[89] Those institutions do exist can be described as structures of control—layered institutional and technological advantages that enable control over flows of capital, goods, and data. These layers reinforce one another through positive-feedback dynamics that create path dependence, as captured in Shapiro and Varian's concepts of *network effects* and *lock-in*.[90] On the importance of technological capacity to the ownership and control of data, de Beer notes that "the physicality of data-related systems cannot be ignored when considering ownership issues."[91]Janzen further emphasizes that, without formal property rights, control is tantamount to ownership: "There are companies out there that say 'yes, you own the data,' but when you read the agreements you find out that they have an unlimited licence to do whatever they want with the data. They own it from the standpoint that they can do whatever they want with it."[92] Indeed, in lieu of formal legal structures to delineate ownership in ag-data, *de facto* ownership falls to the agribusinesses that collect, store, and control ag-data.

This is the status quo. Ellixon and Griffin noted that, as of 2016, "no existing laws cover farm data ownership or implications of misappropriation of that data."[93] Three years later, there is no evidence that this has changed within any legal jurisdiction, whether in Canada, the United States, Australia, or within the EU or its member countries.[94] Responding to a webinar question asking whether "a machine [could] track and send data to the manufacturer without the owner's consent [or knowledge]," agricultural lawyer Todd Janzen confirmed that, "[f]rom [his] research, the general answer to this question [was] 'yes'." However, he also recognized a few potential exceptions pursuant to some US state laws where ag-data contain "personally identifiable information" or where "unauthorized data sharing" has occurred.[95] In Canada, there appear to be no laws on the books that would limit the ability of agribusinesses to use or share ag-data from Canadian farms. In

[88] Janzen, "USDA and Ag Data."
[89] Janzen, "What Makes Ag Data 'Ownership' Unique."
[90] Shapiro and Varian, *Information Rules: A Strategic Guide to the Network Economy*.
[91] de Beer, "Ownership of Open Data: Governance Options for Agriculture and Nutrition."
[92] McIntosh, "The Legal Mess of Farm Data Ownership."
[93] Ellixson and Griffin, "Farm Data."
[94] GDPR does not cover ag-data, as later sections will discuss.
[95] Janzen, "Can an Ag Tech Provider Collect Data without Your Consent?"

an email response to an inquiry from The Western Producer, the Office of the Privacy Commissioner responded only that 'deceptive marketing provisions' under the Competition Act "may apply" to firms using ag-data without the consent of the relevant producer, adding only that "[b]ig data can have implications for other policy areas beyond competition law but the Bureau must restrict its activities to its mandate as set out in the Competition Act" and that "[t]he Bureau has not brought any cases specifically addressing the misuse of data in the farming industry."[96] In response to the same inquiry from The Western Producer, Agriculture and Agri-food Canada stated that "[h]ow the data generated on-farm is used or shared beyond this purpose depends on agreements between farmers and their equipment providers," but that "AAFC has begun consulting with other departments and international organizations to help determine what role government should play."[97]

Many experts have argued that leaving the question of ownership in ag-data to contracts between agribusinesses and producer is insufficient if the goal is to protect and empower producers to share in the value generated by *off-farm* use-cases. Janzen notes that most contracts defining the terms of ag-data ownership use boilerplate user agreements that fail to recognize the way in which ag-data is "is a different type of commodity than the data you have on Facebook or Twitter."[98] According to a recent survey by Farm Credit Canada (FCC), 65% of Canadian producers surveyed did not understand the terms of their contracts with respect to data ownership, though they were highly concerned with "the conditions governing the use and treatment of [their] data by an outside party" (42% considered the issue 'very important' and 29% 'extremely important).'[99] The author of this survey also noted that roughly 80% of respondents chose to provide "additional comments" at the end of the survey (normally, only 30-35% chose to fill out this section), many reporting discontent at discovering that an agribusiness had shared ag-data from their farm without permission[100]

However, even with clearer contracts, the problem remains that agribusinesses are under no obligation to contractually recognize a property interest in ag-data held by producers. When asked his view on the future of ag-data, one founder of an ag-tech startup commented that, under the status quo vis-à-vis ag-data ownership, "the benefits to the farmer at the farm level are going to be very minor," and that "[t]he majority of that value [will] go to the groups that control the flow of data and the analytical service providers."[101] de Beer notes that, generally, without a legal framework to delineate ownership to producers, "[m]ost ownership rights accrue to the intermediaries that invest in databases, not persons who provide or use data."[102]

These comments, and many others from a range of experts, indicate that the status quo may be misaligned with the interests of producers, particularly in the long-term. This suggests a policy gap—

[96] Booker, "The Wild West of Agricultural Data."
[97] Booker.
[98] McIntosh, "The Legal Mess of Farm Data Ownership."
[99] Wall, "Decoding Trust in Data Management in Canada."
[100] Booker, "The Wild West of Agricultural Data."
[101] Sarah, "Big Ag Wants Farmers to Buy Into Satellite Imagery."
[102] de Beer, "Ownership of Open Data: Governance Options for Agriculture and Nutrition."

particularly with respect to ag-data ownership. Further, the opportunity to intervene proactively is now; policymakers should not wait to react to disruption as *secondary* and *tertiary* use-cases emerge. The relevant question is how policy might shape institutions that will limit the potential for exploitation (i.e. *secondary use*) and empower producers to share in future value generated by *off-farm* use-cases (i.e. *tertiary use*).

Figure 3 illustrates the institutional status quo with respect to control over ag-data. Under this institutional framework, agribusinesses excise *de facto* ownership in ag-data through technical, financial, and knowledge advantages. The importance of the technological advantages large agribusinesses hold over individual producers cannot be as "technological measures work along with legal measures to facilitate or frustrate access to data."[103] In most current contracts defining the terms of ag-data use, legal measures weighing in favour of producer ownership are the exception rather than rule, making the discrepancy in technological capacity between agribusinesses and producers all the more relevant. Further, technological capacity is critical not only to controlling ag-data, but also to leveraging it in *secondary* and *tertiary* use-cases. Though farmers hold (and benefit from) the capacity for *primary use*, this only guarantees the continuous flow of ag-data into databases controlled by agribusinesses which—though they may currently lack the capacity for *secondary* and *tertiary use*—are currently miles ahead of producers *technologically* in terms of their readiness to leverage ag-data *off-farm*.

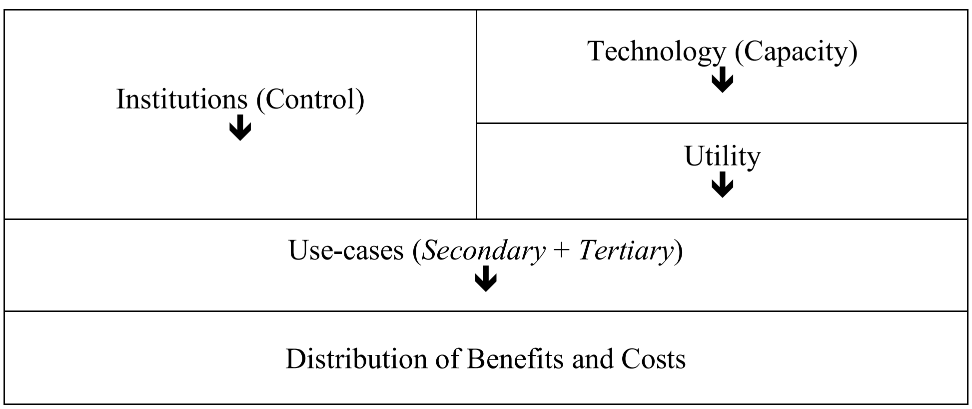

Figure 4.1: The Institutional 'Status Quo'

Figure 3 illustrates how, under the status quo, *institutional* control over and access to ag-data, coupled with the *technological* capacity to leverage ag-data *off-farm*, are the necessary conditions to capture the benefits of digital innovation across the agriculture and agri-food value chain. Today, only agribusinesses and ATPs are in such a position.

[103] de Beer.

4.5 AG-DATA MARKETS: CLASSICAL OR BEHAVIOURAL APPROACH?

It is clear that policy intervention is needed to create an environment wherein agricultural producers can share in the benefits of *off-farm* ag-data use and, by extension, the impending *value chain transformation* of agriculture and agri-food production. The question, then, concerns which institutional mechanisms would create the necessary conditions to achieve a more equitable distribution of benefits, and by extension, greater adoption and diffusion. Under the status quo, agribusinesses hold several massive advantages over producers.

To start, these large, multinational, and often vertically-integrated firms control the technological systems that store and centralize the ag-data collected from thousands of farms; only they can access these troves of ag-data, which are far more valuable in aggregate. Even if it were possible for a handful of producers to withhold or remove the data they generated from these databases, their pooled data would be little more than a drop in the bucket. The major players in agribusiness—whether in biotechnology, agrichemicals, or machinery—occupy a critical position in the commercial ecosystem, which all but guarantees their continued role as the core providers of precision agriculture technologies. Their position is highly centralized while that of each individual producer is diffuse and, thus, negligible. Furthermore, producers operate in a highly competitive environment wherein they must avail all potential advantages to remain profitable. This means adopting precision agriculture technologies will only become more and more critical to their commercial success, a dynamic that is increasingly self-reinforcing as rates of adoption increase.

With respect to governing ag-data, there is no escaping the reality that producers "are already squeezed by the greater market power of their upstream and downstream partners."[104] Although the power of agribusiness firms is centralized while that of producers is diffuse, there are opportunities to "organise data ownership and access so that the position of farmers is improved and not weakened by the new technology," to quote EU Agriculture Commissioner Phil Hogan.[105]

Formal property rights in ag-data may the best mechanism for achieving this goal. Delineating a property interest in ag-data for producers could enable a market structure whereby producers and stakeholders could coordinate to promote positive-sum use-cases for ag-data across the broader value chain. If producers entered this market holding property rights in ag-data, they could choose to exchange their ag-data with agribusinesses for monetary compensation. Provided that the compensation demanded by producers was less than the potential value agribusinesses could generate through *off-farm* use-cases for ag-data, this arrangement could provide an institutional framework for ag-data use that would effectively balance goals of *efficiency* and *equity*.

[104] Michalopoulos, "Hogan."
[105] Michalopoulos.

Figure 4 depicts this improved institutional arrangement, illustrating how the inclusion of property rights held by producers could create the conditions for an ag-data market, which would still allow for the creation of new value (i.e. *efficiency*), but distribute its benefits more *equitably*.

Institutions (Property Rights) ↓	Technology (Capacity) ↓
Ownership ↓	Utility ↓
Starting Position (seller or buyer) ↓	Valuation ↓
Ag-data Markets ↓	
Use-cases ↓	
Distribution of Benefits and Costs	

Figure 4.2: Ag-Data Markets

A handful of nascent ag-data markets (and, by extension, some form of producer ownership in ag-data) already exist today on a direct agribusiness-to-producer basis.[106] Farmobile's 'DataStore' and Decisive Farming's Optimize RX variable rate data platform bothoffer producers payments in the range of $4 per acre for VRT-generated ag-data in malt barley production.[107] In the first case, producers' sale of ag-data is optional and allows them to specify which third-parties are allowed access;[108] in the second case, producers using the OptimizeRX platform necessarily grant use to Decisive Farming, but expressly in the context of researching malt-barley production.[109] These atomized, bilateral market arrangements are the most likely template for early ag-data markets; though one could also foresee more complex, multi-lateral markets involving several producers and agribusinesses, the attending opportunities and risks would also be more complex and difficult to model. The sharing or transacting of ag-data between agri-businesses is another extant form of ag-data market, though such activity—while not illegal (most use contracts that assign producers no property interest in ag-data)—likely occurs privately to avoid scrutiny.

There are many arguments to support the market as a distributional mechanism, many of which focus on their *efficiency* and capacity to manage complexity through what Hayek termed 'spontaneous order,' occurring as "the result of human actions, not of human design."[110] Classical economics, as explicitly

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[106] Begemann, "DataStore Means Farmers Can Sell Data For Real Dollars."
[107] Bartlett, "Decisive Farming Offers Farmers $4 Per Acre For Malt Barley Data."
[108] Schrimpf, "Farmobile Addresses Data Transparency With New Legal Agreement."
[109] Bartlett, "Decisive Farming Offers Farmers $4 Per Acre For Malt Barley Data."
[110] Hayek, *Studies in Philosophy, Politics and Economics*.

formulated in the Coase theorem, holds that delineating clear property rights in ag-data—i.e. rights to use and exclude others from using—would, assuming sufficiently low transaction costs, enable ‘Coasian bargaining’ that would result in Pareto-efficient outcomes.[111] In other words, provided property rights in ag-data are clearly defined, the right to use ag-data would flow, though bargaining, to the party who values them most—i.e. the party capable of using ag-data to generate the greatest economic value, thus producing the most *efficient* (if not necessarily most *equitable*) outcome.

Contrary to the Coase theorem, this thesis posits that assigning property rights in ag-data may prove necessary but not sufficient to realizing the most *efficient* environment wherein ag-data are efficiently leveraged and exchanged. Policy must also appreciate that this environment may elude the standard economic assumption that markets will efficiently coordinate exchanges, regardless of their initial allocation, given clearly-delineated property rights.[112] Potential behavioural dynamics underlying ag-data exchange between producers and agribusinesses may impede Coasian bargaining, resulting in outcomes that are neither *efficient* nor *equitable*. This could mean that it matters, in terms of not only *equity* but *efficiency*, to whom property rights in ag-data are initially assigned; even that the notion of ag-data markets itself is fraught with problems grounded in the dynamics of behaviour.

Approaching this question, it is sensible to start with producers, who, in the early stages of digitization, have the least information with which to accurately value ag-data generated from their operations. Though producers are compelled by the demands of end-consumers and face pressure from both ends of the value chain, they retain significant agency over their commercial and production decisions. Producer actions and decisions animate myriad, seasonal, ag-production cycles that overlap at staggered intervals across diverse geographies. Complex sets of individual producer decisions determine the composition of the global food supply to the extent that producers retain the prerogative to decide which crops they grow, when, and using which tools; the sum of their individual choices dictates, in part, the availability and nutritional content of the food staples consumed across the globe.[113]

Therefore, the choice architecture of decisions that producers face *on*-farm—and their personal attributes affecting these decisions—could matter in the context of bargaining. North American producers are characteristically independent and shrewdly skeptical of unproven technologies.[114] Yet technology is core to their production activities, which frequently absorb early waves of technological diffusion.[115] The adoption rate of *on-farm* innovations, as well as how producers use these tools, determines the volume, variety, and velocity

[111] Coase, “The Problem of Social Cost.”
[112] Coase.
[113] Wolfert et al., “Big Data in Smart Farming – A Review.”
[114] Sullivan, Interview with Bryan Sullivan, Farmer.
[115] Mulla, “Twenty Five Years of Remote Sensing in Precision Agriculture.”

of ag-data generated. This edifice of ag-data rules shapes future possibilities for *value chain* ag-data use and its consequent pathways for creative destruction.[116]

Various literatures have investigated producer adoption of *on-farm* technologies.[117] Instead, this thesis aims to simulate producer decision-making in a notional market for ag-data—data generated from *their* farm and through *their* production activities. It is likely that a complex array of behavioural dimensions influence producers' valuation and decisions related to ag-data. However, for policymakers, a sensible starting point may be to simulate how producers would behave were property rights clearly delineated. This thesis applies a behavioral approach to one piece of the larger policy puzzle, considering the question of whether initial assignment of ownership affects outcomes in an environment wherein ag-data are transacted—or, as characterized in the seminal work of Kahneman and Tversky, and at the heart of many behavioural questions, 'Does starting point matter?'[118] Behavioural science asserts that when this question is answered affirmatively we are observing an *endowment effect*—i.e. when the condition of ownership, itself, leads the owner to irrationally overvalue an asset *qua* possession.[119] Inversely, the *endowment effect* could be construed in terms of the condition of non-ownership, where the non-owner undervalues an asset when faced with the choice to purchase said asset.

Determining if and to what extent the endowment effect factors into ag-data transactions could greatly help policymakers understand, in terms of both *efficiency* and *equity*, the potential impacts of delineating ag-data ownership to producers versus agribusinesses and whether Coasian bargaining alone could work with that assignment to realize outcomes that align with the public interest. To that end, this thesis advances a behavioral experiment, surveying a large classroom of agriculture students—a proxy for Canadian producers—at the University of Saskatchewan to test their decision-making vis-à-vis transacting ag-data. The presence of an endowment effect, and the impact of *worldviews* thereon, would suggest that the initial allocation of property rights over ag-data would (or already does) influence outcomes in markets for ag-data (existing or imminent). Getting clearer answers to these questions could help policymakers better understand whether Coasian bargaining can be expected to result in an *efficient* allocation of property rights in ag-data.

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[116] Pfarrer and Smith, "Creative Destruction."
[117] Aubert, Schroeder, and Grimaudo, "IT as Enabler of Sustainable Farming."
[118] Kahneman, *Thinking, Fast and Slow*.
[119] Hayes, "Endowment Effect."

CHAPTER V. THE BEHAVIOURAL APPROACH

5.1 OVERVIEW

Whereas other schools of economics focus primarily on conditions outside the individual (e.g. laws, endowments, capabilities, etc.) that shape markets and determine market outcomes, behavioural economics considers how the structures of the human mind respond to particular sets of external conditions (i.e. the 'choice architecture' or 'framing' of individual economic decisions). Studying these cognitive structures has revealed a stunning range of predicable 'systematic biases' in human cognition.[120] Understanding and accounting for these biases in policymaking can help improve the quality of economic policies.

The previous section identified that *institutionally* the status quo would benefit from formal proprietary definition. This thesis confronts the question of how policy could better structure and define, delineate, and allocate property rights in ag-data. Classical economics holds that, if policy added greater proprietary definition to ag-data markets, rational actors, regardless of the initial assignment of ownership, will transact to *efficiently* allocate property rights. However, this view contradicts a considerable body of evidence from experiments in the behavioural literature showing that actors often make very different transactional decisions depending on whether they own the item in question. This section reviews the behavioural literature on the endowment effect and its influence on bargaining as well as the literature on 'worldviews' as a secondary behavioural component.

5.2 THE ENDOWMENT EFFECT

A defining assumption in classical economics is that individuals, given sufficient information, will behave in markets as rational actors, seeking to maximize their individual utility (often based on individual preferences) under whichever circumstances they may face. This assumption confers a large measure of predictability of individual behaviour such that modelling various economic scenarios need only consider parameters for individual preferences and external economic conditions. Contrarily, behavioural economics acknowledges not only the relevant individual preferences and external conditions, but also how individuals perceive or contextualize information about these external conditions (i.e. framing).

In bargaining scenarios, the classical economic assumption is that the difference between 'willingness to pay' and 'willingness to accept' should be negligible.[121] However, in a 1980 paper seminal in establishing behavioural economics, Thaler identified a pattern he dubbed the endowment effect—"the fact that people

[120] Kahneman, *Thinking, Fast and Slow.*
[121] Willig, "Consumer's Surplus Without Apology."

often demand much more to give up an object they would be willing to pay to acquire it."[122] This paper strongly challenged the assumption that entitlements do not impact valuation by showing that, under certain circumstances, individuals' selling prices considerably exceed their buying prices. One example showed that "the minimal compensation demanded for accepting a .001 risk of sudden death was higher by one or two orders of magnitude than the amount people were willing to pay to eliminate an identical existing risk."[123] Thaler has since demonstrated many examples of the endowment effect, "especially for goods that are not regularly traded."[124]

A year before Thaler's 1980s thesis establishing the 'endowment effect,' two of behavioural economics' other founding fathers, Kahneman and Tversky, had published their own defining work in the discipline. "Prospect Theory: An Analysis of Decision under Risk" introduced the concept of 'loss aversion,' "the generalization that losses are weighted substantially more than objectively commensurate gains in the evaluation of prospects and trades."[125] Their new 'prospect theory' challenged the 'expected utility theory' from classical economics and, by extension, the "wide acceptance of the Coase theorem assertion that, subject to income effects, the allocation of resources will be independent of the assignment of property rights when costless trades are possible."[126] Prospect theory provided a theoretical context for Thaler's observations of the endowment effect and "other puzzles in his collection,"[127] by explaining how and why the reference point for individuals valuing an asset differs greatly depending on whether they stand to 'gain' or 'lose' that asset. Kahneman and Tverkey's explanation was that, due to 'loss aversion,' individuals making a transactional decision weigh the 'pain' of losing an item more than the 'pleasure' of acquiring that same item and, thus, value it more under the condition of ownership.[128]

Years later, Kahneman and Thaler would collaborate (along with Canadian economist Jack Knetsch) to further develop the concept of the endowment effect. Their 1991 paper, "Experimental Tests of the Endowment Effect and the Coase Theorem" deals explicitly with the implications of loss aversion in the context of bargains, challenging the 'expected utility theory' that underpins the Coase theorem and its conclusions about the minimal conditions necessary to produce efficient market outcomes.[129] The 1991 paper distinguishes between the effects of loss aversion and other factors that would potentially contribute to "discrepancies

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122 Thaler, "Toward a Positive Theory of Consumer Choice"; Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem."
123 Thaler, "Toward a Positive Theory of Consumer Choice"; Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem."
124 Kahneman, *Thinking, Fast and Slow*.
125 Kahneman and Tversky, "Prospect Theory"; Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem."
126 Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem."
127 Kahneman, *Thinking, Fast and Slow*.
128 Kahneman.
129 Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem."

between the evaluations of buyers and sellers,"[130] such as the perceived illegitimacy of a transaction the part of the prospective seller,[131] standard bargaining habits,[132] and actors habitually misrepresenting their true valuations as a sheer strategic mistake.[133] By contrast, loss aversion is understood to produce this discrepancy in valuations not as an intentional distortion or misrepresentation of value, but rather a deeper, fundamental difference in individual preference caused by their initial endowment (or lack thereof).

The 1991 paper also introduced the critical distinction between items held "for exchange" versus those held "for use."[134] Loss aversion does not (at least, as forcefully) influence an individual's valuation of an item held for 'exchange,' which, by definition, the owner intends to hold only temporarily, all the while perceiving it as merely "a cumbersome proxy for money that he was hoping to collect from the consumer" (e.g. how the owner of a shoe store views the shoes in his or her inventory).[135] On the other hand, though the owner of an item held 'for use' would not experience loss aversion when faced with the decision to acquire an item (e.g. when buying a pair of shoes from a shoe store), the same owner would experience loss aversion if faced with the decision to sell that same item he or she had just acquired 'for use' (e.g. if a friend offered to buy the same 'brand-new' shoes from the original purchaser).

This notion of items held 'for exchange' versus 'for use' is pertinent in the context of this thesis, whose primary hypothesis is that agricultural producers' will value property rights in ag-data more if they enter the bargain as owners. In more formal terms, this thesis conveys an analysis that tests for the presence of the endowment effect, which, as explained above, occurs when the condition of ownership itself leads the owner to irrationally overvalue an asset or possession (in this case, property rights in ag-data).

For several reasons, ag-data are to be considered as the subject of bargaining. Both producers and agribusinesses 'use' ag-data in a 'primary' capacity, so both should regard it as an item held 'for use' rather than 'for exchange.' In the 'for use' context, ag-data's value is determined by the utility its use can produce for the owner; in turn, the utility it can produce for its owner depends on the owner's technological capacity to apply the ag-data to a productive use-case. While the producer has the capacity to use and derive utility from ag-data *on-farm* (i.e. precision agriculture), only (some) agribusinesses likely hold the capacity to use (i.e. derive utility from) ag-data through *off-farm* use-cases. So, regarding a producer selling property rights in ag-data to an agribusiness for use in an *off-farm* capacity, the question becomes whether the producer would

130 Kahneman, Knetsch, and Thaler.
131 Rowe, D'Arge, and Brookshire, "An Experiment on the Economic Value of Visibility."
132 Knez, Smith, and Williams, "Individual Rationality, Market Rationality, and Value Estimation."
133 Coursey, Hovis, and Schulze, "The Disparity Between Willingness to Accept and Willingness to Pay Measures of Value"; Brookshire and Coursey, "Measuring the Value of a Public Good."
134 Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem"; Kahneman, *Thinking, Fast and Slow*.
135 Kahneman, *Thinking, Fast and Slow*.

regard the same ag-data as an item held 'for exchange' so long as he or she can continue using ag-data in a *primary* capacity?

Indeed, in general, data are unique assets in that the same data are infinitely replicable: the same information can be copied infinitely for use by as many individuals as can access their own copy. However, much like other intangible assets (e.g. intellectual property rights), use of a dataset can be rivalrous (i.e. one's use of data toward a particular end could reduce the utility of another's use of that same data). Therefore, the value of property rights in ag-data lies in the owner's ability to not only use these data but also (through force of property law) to exclude others from using it in ways contrary to the owner's interests (in the case of this thesis, 'secondary use'). This is relevant in that that some *off-farm* use-cases for ag-data pose the risk of generating utility for the agribusiness and disutility for the producer (i.e. *secondary use*). Therefore, whether in the context of *on-farm* or *off-farm* use, a producer will likely regard ag-data as an item held 'for use' rather than 'for exchange,' regardless of the use-case. Therefore, it is a reasonable hypothesis that producers with a property interest in ag-data could experience loss aversion in the context of bargaining.

5.3 WORLDVIEWS

Beyond the endowment effect, this thesis also explores whether producers' 'worldviews' attenuate the presence of the endowment effect in their transactional decision-making. The concept of 'worldviews' demands some elaboration. The cultural cognition literature may represent the most sophisticated effort to examine the impact of worldviews on decision-making, particularly in the context of risk perception, scientific consensus, and public policy.[136] Though its contributions are certainly pertinent to the questions at hand, this thesis instead adopts a less-explored theoretical framework defining worldviews. This framework originates from Gilpin in the international political economy (IPE) literature, further developed in respective contributions from Cohn and Phillips.[137]

The field of IPE emerged in the early 1970s based on recognition of the need to further integrate the study of international politics with that of an increasingly globalized economy. Early contributions from Strange, Cohn and Gilpin, among others, noted a greater need to account for the interrelationship between not only states, but also "multinational corporations, interest groups and international political and trade regimes that render the traditional state-market and international-domestic dichotomies insufficient frameworks for analysis."[138]

[136] Kahan, "Ideology, Motivated Reasoning, and Cognitive Reflection"; Kahan and Braman, "Cultural Cognition and Public Policy"; Kahan, Jenkins-Smith, and Braman, "Cultural Cognition of Scientific Consensus"; Kahan et al., "The Polarizing Impact of Science Literacy and Numeracy on Perceived Climate Change Risks"; Kahan et al., "Cultural Cognition of the Risks and Benefits of Nanotechnology."
[137] Cohn, *Global Political Economy*.
[138] Boland et al., "Collaboration and the Generation of New Knowledge in Networked Innovation Systems."

A handful of years into the early development of the IPE literature, Gilpin's 1975 article "Three models for the future" recognized that three distinct empirical and normative camps had begun to coalesce within the literature, each incorporating its own theoretical influences from prior scholarship in political science, economics, and political theory to the fledgling discipline of IPE.[139] Gilpin proposed that each camp offered not only their own unique analytical approach to understanding current developments in the international political-economic order, but also three unique 'models for the future' (with respect to both ongoing scholarship and the policy prescriptions flowing therefrom): "These models are really representative of the three prevailing schools of thought on political economy: liberalism, Marxism, and economic nationalism. Each model is an amalgam of the ideas of several writers who, in my judgment (or by their own statements), fall into one or another of these three perspectives on the relationship of economic and political affairs."[140]

Gilpin defined liberalism by the view that "increasing economic interdependence and technological advances in communication and transportation" had "undermined the traditional economic rationale of state," further characterizing that "in the interest of world efficiency and domestic economic welfare, the nation state's control over economic affairs will continually give way to the multinational corporation" and "other international institutions better suited to the economic needs of mankind."[141] Next, Gilpin defined Marxism (or the 'dependencia model') by its conception of a "hierarchical and exploitative world order" in which "the flow of wealth and benefits," through the same mechanisms of globalization heralded by liberals, "from the global, underdeveloped periphery to the centers of industrial financial power and decision."[142] In essence, the Marxist camp views what liberals conceive as 'transnationalism' to really be a form of 'imperialism' disguised as benevolent liberalization of global markets. Last, Gilpin defined economic nationalism (or 'the mercantilist model'), in contrast to both liberalism and Marxism, as maintaining a view of the nation-state as the dominant player in the international political-economic order and "the interplay of national interests (as distinct from corporate interests) as the primary determinants of the future role of the world economy."[143]

Gilpin's tripartite characterization of the study of IPE has proved to be a durable framework for understanding not only the IPE literature, but also contemporary political and economic debates characterized by rising populism, technological displacement, and the changing dynamics of global trade. Cohn's defining textbook on IPE, "Global Political Economy: Theory and Practice," continued Gilpin's tripartite framework, accounting more fully for the prior theoretical underpinnings of each while also capturing how each has developed throughout the evolution of IPE as a literature.[144] Gilpin's 'economic nationalism' was broadened to

[139] Gilpin, "Three Models of the Future."
[140] Gilpin.
[141] Gilpin.
[142] Gilpin.
[143] Gilpin.
[144] Cohn, *Global Political Economy*.

embrace the canon of 'realism' in the field of international relations, with roots extending as far back as Thucydides, through Machiavelli, Alexander Hamilton, and up to early 20th Century thinkers like Keynes, and later ones like Morganthau, Waltz, and Kissinger. Similarly, Cohn broadened Gilpin's conception of liberalism, rooting it in the tradition established by Adam Smith and John Locke, later inherited and developed in the work of 20th century neo-classical economists like Hayek and Friedman. Finally, Cohn developed Gilpin's concept of Marxism well beyond its namesake to incorporate, among many others, the related thought of Gramsci, Wallerstein, and several scholars in the broader feminist and critical literatures.[145]

This thesis attempts to adapt this tripartite schema from the international relations and IPE literatures to a novel context: the worldviews of agricultural producers and their opinions of the influence of transactional decision-making on ag-data. It may seem a leap to assert that the descriptive and normative commitments of scholars in a particular academic discipline constitute an appropriate framework in which to categorize the 'worldviews' or ideological commitments of individuals far removed from the original context; this thesis fully admits to the preliminary and experimental nature of this exercise, which, at this point, is intended as nothing else. Nonetheless, the intuitiveness of Gilpin's tripartite framework suggests that the bundles of ideological commitments encapsulated in each of the three categories could, to some extent, align with those held by others (including agricultural producers). This thesis recasts the three categories into the following template:

- The *realist* worldview is characterized by prioritization of the state, state power, zero-sum dynamics, nationalism, politics over economics, a mercantilist view of trade and globalization, and a state-driven process of innovation and economic development. Today, the global rise of nationalism and a shift in global trade toward protectionism led by the US under the presidency of Donald Trump best exemplify the *realist* worldview in the contemporary context.
- The *liberal* worldview is characterized by prioritization of the individual, economic power, positive-sum dynamics, individualism, privileging economics over politics, a laissez faire view of trade and globalization, and a market-driven process of innovation and economic development. Liberalism has been the dominant global force in the post-WWII global order, strengthening under the neoliberal reforms of the 1980s and with the fall of communism that ended the Cold War. However, the international liberal order is today challenged by the same forces of nationalism and protectionism.
- The *critical* worldview prioritizes identity-based groups, relational power between groups, negative-sum dynamics, group identity, a conflictual view of politics and economics, a dependency-based view of trade and globalization, and the need for socially-directed goals for innovation and economic development.

[145] Cohn.

CHAPTER VI. METHODS AND HYPOTHESIS

6.1 STUDY OVERVIEW

This study employed a behavioural methodology to test for the presence of an endowment effect in subjects' valuation of ag-data. An online survey instrument was chosen to effectively reach a statistically significant sample and establish a controlled environment appropriate for measuring the behaviour of respondents. Care was taken to ensure that, throughout the survey, exposure to information was consistent and neutral, the goal being to provide sufficient context to simulate the real-world experience of an agricultural producer engaged in a bargaining scenario. The survey's primary objective was to measure the impact of the endowment (the key independent variable) on producers' valuation of ag-data (the key dependent variable). The secondary objective was to measure the strength of respondents' propensity toward one of three worldviews (secondary independent variable) and its impact on their valuations of ag-data. The experiment and survey instrument were designed and programmed in consultation with the Social Science Research Lab at the University of Saskatchewan.

This SSHRC-funded experiment received full ethics approval from the University of Saskatchewan Research Ethics Board. Voxco, a Canadian-owned and managed company whose data is securely stored in Canada, digitally hosted the survey. All user data from respondents was anonymized and no foreseeable risks were identified in the ethics approval process.

6.2 EXPERIMENT DESIGN

The primary objective of the behavioural experiment was to test for the endowment effect in respondents' valuation of ag-data. To avoid order effects (e.g. fatigue, unintended knowledge), the experiment adopted a between-group design whereby the repsondents were randomly assigned to one of two treatments. The first treatment (T1) measured respondents' 'willingness to accept' while the second treatment (T2) measured respondents' 'willingness to pay.' Given the between-group experiment design, the language of each treatment differed minimally (i.e. only enough to convey the intended meaning) in order to control for the distinct effect of each treatment in isolation from arbitrary differences that could introduce noise into the results. Further, the experiment was designed to conceal from respondents its true purpose (to measure for the presence of the endowment effect): by definition, the endowment effect can exist only insofar as a subject remains unaware of its influence on their valuation process. Thus, respondents were provided no prior introduction to the concept of the endowment effect (or biases in decision-making, more generally), nor were respondents informed that they would receive one of two opposing treatments. The experiment was conducted via an online survey instrument, which contained four main components. Each survey component was tested in advance with classmates and other volunteers to ensure the intended meaning was successfully conveyed in the language used.

6.2.1 The Experiment Brief

The first survey component was a short 325-word 'Experiment Brief' designed to situate the respondent in the context of an agricultural producer making a transactional decision regarding the transfer of property rights in ag-data. Excerpted fully in Figure 5, the brief conveyed that the object of this bargain was ag-data generated from the respondent's own farming operation. The language was carefully chosen to subtly suggest potential (but uncertain) risks associated with an agribusiness owning the respondent's ag-data. This subtlety was critical to avoid 'leading' the respondent toward overemphasizing risk (i.e. 'secondary ag-data use') over benefit (i.e. money) in their decision making. Each respondent, whether assigned to T1 or T2, received the same brief to 'calibrate' him or her before the experiment, whereupon the total sample group was split roughly in half. Calibration increased the likelihood that differences in the results from each group resulted from their respective treatments rather than from irrelevant characteristics between participants (e.g. the varying degree of subject knowledge among respondents). Last, the brief was designed to inform, but not exhaust, the reader such that he or she was maximally engaged in the subsequent experiment.

> Before the experiment, it is very important that you have a bit of background information. We would like you to imagine that you are a farmer facing new decisions and challenges in today's increasingly data-driven world:
>
> As a farmer, new digital technologies enable you to bring science to the management of your farm. Data enable you to understand the relationships between complex variables (e.g. soil, seed, chemical inputs, yield and quality), which can help you make better decisions and increase your productivity and efficiency. We will call these on-farm activities the 'primary use' for ag-data. As a leading-edge farmer, you generate and use vast amounts of data each season. Your data is likely also very valuable to agribusiness firms whose businesses would benefit from having this information (e.g. yield, soil conditions, input decisions, etc.). While it is clear how data is used on-farm to improve production, less is known about how data can be used off-farm by agribusinesses in other activities (e.g. marketing, manufacturing, market speculation, etc.). We will call any such activates by agribusiness firms 'secondary uses' for ag-data.
>
> These secondary uses raise questions about data ownership, which is defined as an exclusive right to control how others can use data. In other words, if you (the farmer) own data, you have the right to prevent agribusinesses from using it in ways that may go against your interests. Ownership also means that you reserve the right to negotiate a fee if companies wish to use your data for any secondary activities; if they are not willing to pay, you can deny them access to the data. On the other hand, if an agribusiness company owns this data, they are free to use it in whichever ways might benefit their business. In this scenario, they may allow you to use the data generated on your farm if you are paying for their precision-ag software, but the data is ultimately theirs to decide what to do with.

Imagine that you own and operate a large area farm producing crops in Western Canada. In the last decade, you have successfully managed this operation and, each year, your level of comfort with precision farming technologies continues to grow. You exclusively use AgManufacturing Co. equipment and recently adopted their fully-integrated precision agriculture suite, AgPrecisionTM. This investment has significantly increased your yields while, at the same time, reducing chemical use and associated costs. As you collect more data each season, you learn more about your land and how to farm it most efficiently. Given all the success you have experienced, you intend to continue using this technology in the upcoming season.

Figure 6.1: The Experiment Brief

6.2.2 The Endowment Effect

The second survey component was the behavioural experiment, which randomly assigned roughly half the sample group to T1 and the other half to T2. The experiment was positioned as early as possible in the survey to avoid behavioural measurements being tainted by the influence of subsequent 'worldview' questions. The experiment simulated a scenario wherein respondents were asked to imagine themselves as producers participating in a market for ag-data in which a large agribusiness firm (i.e. "Company X") was their counterparty. In this market, each respondent (qua producer) was asked to value the ag-data based on very limited information about potential risks associated with Company X owning ag-data from the respondent's farm. Conversely, the monetary value associated with transferring ownership (i.e. either paying to buy or receiving to sell) was known to the participant.

Treatment #1

Imagine that *you* currently own all data produced by your farm. This means that you have the right to disallow *AgManufacturing Co.* from using your data for any purposes unrelated to delivering AgPrecision™.

This morning, you received an email from *AgManufacturing Co.* indicating that they wish to pay you for ownership of your farm's data. If you wish to transfer ownership, you would be paid *x* dollars per acre for each year data have been collected in the past. Additionally, you would receive *x* dollars per acre for every upcoming season data is produced by your farm.

The transfer of ownership is completely optional. What is the lowest price at which you would still be willing to sell *AgManufacturing Co.* rights to your farm's data?

Various experts have estimated that a price ranging between $3-18 / acre reflects fair market value for these data.

Imagine that each price is the only deal offered; please choose the lowest price you would still be willing to accept.

$0 / acre
$3 / acre
$6 / acre
$9 / acre
$12 / acre
$15 / acre
$18 / acre
More than $18 / acre

Figure 6.2: Treatment 1

T1 assigned property rights in ag-data to the participant (qua producer) and asked the *minimum price* at which he or she would be willing to transfer ownership to Company X. Conversely, T2 assigned property rights in ag-data to Company X and asked the *maximum price* each participant would be willing to pay to acquire ownership. Under both treatments, respondents were presented with a range of dollar values, per acre of land, for ag-data rights. The options ranged from a minimum of '$0' to a maximum of 'more than $18', with the interval variable scaled in increments of $3.

As demonstrated in the excerpted survey questions (Figures X & Y), Treatments 1 and 2 differed only enough to convey the opposite initial assignment of ownership in ag-data (language otherwise differed minimally). The decision facing the respondent was not one of a set of iterated transactions (for a finite volume of ag-data), but rather a one-off transaction for all ag-data, past and future, generated as long as the respondent (qua 'producer') continued to use technology supplied by Company X.

Treatment #2

Imagine that *AgManufacturing Co.* currently owns all data produced by your farm. This means that *AgManufacturing Co.* has the right to use your data for any purposes.

This morning, you received an email from *AgManufacturing Co.* indicating that they wish to give you the option to buy ownership of your farm's data. If you wish to acquire ownership, you would pay *x* dollars per acre for each year data have been collected in the past. Additionally, you would pay *x* dollars per acre for every upcoming season data is produced by your farm.

The transfer of ownership is completely optional. What is the highest price you would be willing to pay *AgManufacturing Co.*to acquire rights to your farm's data?

Various experts have estimated that a price ranging between $3-18 / acre reflects fair market value for these data.

Imagine that each price is the only deal offered; please choose the highest price you would still be willing to accept.

$0 / acre
$3 / acre
$6 / acre
$9 / acre
$12 / acre
$15 / acre
$18 / acre
More than $18 / acre

Figure 6.3: Treatment 2

6.2.3 Worldviews

The third survey component presented nine questions designed to capture the strength of respondent's orientation toward one of three worldviews (i.e. *Realist, Liberal,* and *Critical*). Respondents were assigned one point for each answer that corresponded to one of the three worldviews. Table 1 provides the template that informed each of the nine 'worldview' questions.

Question	**Issue**	**Worldview**		
		Realist	**Liberal**	**Critical**
Q1	*International Free Trade*	It has some benefits but should be limited where it causes domestic problems (e.g. regional unemployment, security risks, or erosion of national independence).	It increases overall wellbeing and states should trade as openly with one another as possible.	It primarily benefits those who are already wealthy, deprives working people of their jobs, and perpetuates.

Q2	*R&D and Innovation*	Canada should invest heavily and take a large role in setting the R&D and innovation agenda.	Most impactful R&D and innovation takes place in the private sector and the agenda should be determined by consumers in the market.	R&D and innovation should be aimed primarily at addressing social issues.
Q3	*Best represents Your Interests*	The Canadian government	The market	Community-based groups (e.g. NGOs, co-operative enterprises)
Q4	*Most Important When Purchasing Food*	That it is produced in Canada and strengthens our economy	That I can buy it at the lowest possible price	That it is ethically-sourced and produced with minimal negative impact
Q5	*Globalization*	Despite some positive consequences, it has undermined Canada's ability to protect national interests and has been detrimental to national culture.	It has enriched the world both culturally and economically and has improved the wellbeing of most people across the globe.	Despite some positive consequences, it has perpetuated and deepened inequalities between different groups
Q5	*Personal Identity*	Canadian citizen	Individual	Part of a group (class, ethnicity, gender, sexual orientation, or intersection thereof)
Q6	*Core principle*	Public Service	Individual Liberty	Social Justice
Q7	*Best justification for limiting privacy*	National security (e.g. national surveillance to protect against terrorism)	Efficiency, convenience and personalization (e.g. automatic sharing of personal data to increase ease of use)	Equality and social justice (e.g. use of social media to 'call-out' people ostensibly guilty of sexual misconduct)
Q8	*3 most serious problems facing the world*	• Competition from emerging economies • Terrorism and security issues	• National debt and public overspending • Protectionism and collapse of free trade agreements	• Growing income inequality • Systemic oppression of marginalized groups
		Worldview-neutral options: • aging populations • climate change • nuclear proliferation • increasing global population		• poverty, hunger and lack of clean drinking water • spread of infectious disease • other (please specify)

Table 6.1: Worldview Survey Questions

Most questions offered only three answers; only Q8 provided several worldview-neutral options as well as two options representing each worldview. One point was counted for each answer corresponding to a respective worldview, except in Q8 (where maximum of two points could be counted toward each worldview). To reiterate, the purpose of this section was to probe, first, whether the *worldview*, unto itself, constitutes an independent variable impacting data valuation and, second, whether *worldviews* constitutes an intervening variable that attenuates the endowment effect, positively or negatively.

6.2.4 Demographic Questions

The fourth and last survey component presented seven demographic questions related to age, gender, ethnicity, academic program, and personal background vis-à-vis agriculture. The entire survey lasted no longer than 30 minutes in duration.

6.3 RECRUITMENT & SAMPLE

The study drew respondents from a class of undergraduate students enrolled in the College of Agriculture and Bioresources at the University of Saskatchewan. The session, on March 8th 2018, began with a brief introduction to the study of 'decision-making' delivered by Dr. Peter Phillips. Immediately thereafter, the primary researcher (i.e. the author of this paper) briefly instructed the group of respondents to digitally access the survey on their computers or phones. All respondents completed the survey within the remaining duration of the class.

The population of interest was agricultural producers; undergraduate agriculture students served as a proxy for this population. As depicted in Table 2, the sample population contained 137 respondents, 67 of whom received T1, 70 of whom received T2. Assignment to T1 or T2 was digitally randomized.

Group	Sample Size
T1	67
T2	70

Table 6.2: Sample Distribution

6.4 HYPOTHESIS

The endowment effect occurs when the condition of ownership, itself, leads the owner to overvalue an asset or possession (in this case, property rights in ag-data). A purely rational individual should determine a valuation for ag-data based on the best available evidence; endowment should play no role in their decision-making process. Under T1, such a rational individual should choose to sell ag-data rights only for a price higher than his or her pre-calculated, rational valuation and, under T2, choose to acquire ag-data rights only for a price lower than his or her pre-calculated, rational valuation. In the context of a producer transacting ag-data, the relevant determinants in valuation should be (1) the value he or she can leverage from the leveraging the relevant ag-data and (2) the potential risks he or she can mitigate through retaining the right to exclude agribusinesses from *secondary use*. However, due to the uncertainty surrounding how ag-data could be used *off-farm* (i.e. the impacts of *secondary* and *tertiary* use), producers cannot accurately determine the true value of ownership and must, instead, transact largely based on irrational, biased decision making.

Therefore, the null hypothesis predicts a negligible difference in valuation between respondents under T1 from those under T2 (i.e. the pre-assignment of ownership will not influence the valuation of a perfectly rational actor). This thesis tests the alternative hypothesis that mean valuation of respondents under T1 will differ from the mean value of participants under T2 to a statistically significant degree (i.e. agricultural producers will value property rights in ag-data more if they enter the bargain as owners). Chapter VII explores the results of this experiment.

6.5 LIMITATIONS

Though significant thought and attention were devoted to experimental design, it is important to note a few potential limitations. First, the scenario the experiment intends to convey is somewhat complex with respect to the precise meaning of 'transferring ownership' in ag-data. Specifically, the language of the experiment intends to convey a scenario wherein ownership pertains to a right to exclude other actors from using ag-data as an input *off-farm* use cases. Thus, T1 respondents face the choice to exchange, for monetary compensation, this right to exclude an agribusiness from using their ag-data in any *off-farm* capacity. However, the scenario intends to also convey that, after transferring ownership, the producer (i.e. respondent) may continue using this (and future) ag-data *on-farm* in precision agriculture activities, which is what drives the continuous generation of ag-data in the first instance.

The concern is that, due either to perceived ambiguity in the experimental language or the sophistication of the scenario, respondents in either treatment group could arrive at differing interpretations of what precisely what they stand to gain or lose. This could be particularly problematic with respect to T1 if respondents differed in their respective interpretations of 'transferring ownership' over ag-data. This could cause the determinants of loss aversion to be stronger for some participant and weaker for others, ultimately producing an unreliable measurement of the endowment effect. Though considerable pre-testing of the survey instrument did not provide cause for such concerns, they should nevertheless be noted as potential limitations.

A second potential limitation concerns the presentation of price options in the experiment, which appear in a column with '\$0 per acre' at the top and 'More than \$18 per acre' at the bottom. Here, the concern is that, because people reliably read from top to bottom, the appearance of '\$0' as the first number could produce an anchoring effect that biases respondent valuations toward lower values. Though an anchoring effect is possible and the experiment could have considered alternative presentations, this concern is lessened by the fact that the anchoring bias would likely apply consistently across both treatment groups insofar as T2 respondents would tend equally to read the answers from top to bottom, thereby also starting with '\$0 per acre.'

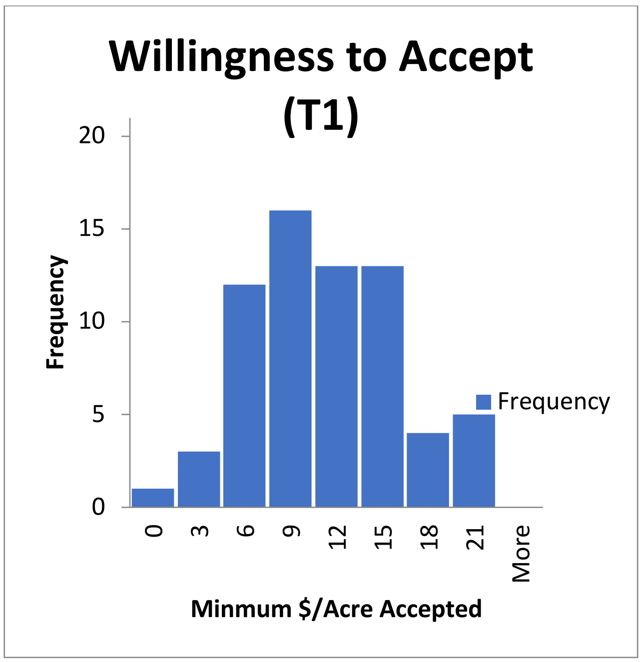
Overall, neither potential limitation presents enough concern to undermine our confidence in the validity of the experiment as a tool to reliably measure the endowment effect in respondents across the two treatment groups.

CHAPTER VII. RESULTS & ANALYSIS

7.1 PRIMARY ANALYSIS: ENDOWMENT EFFECT

7.1.1 Results

Figure 8 displays the sample distributions for Treatments 1 and 2. A side-by-side comparison clearly reveals that respondents under Treatment 1 tended toward higher valuations than respondents under Treatment 2. Whereas Treatment 1 features a concentration of valuations in the range of $6-15 per acre, in Treatment 2, a concentration consists in the range of $3-9 per acre.



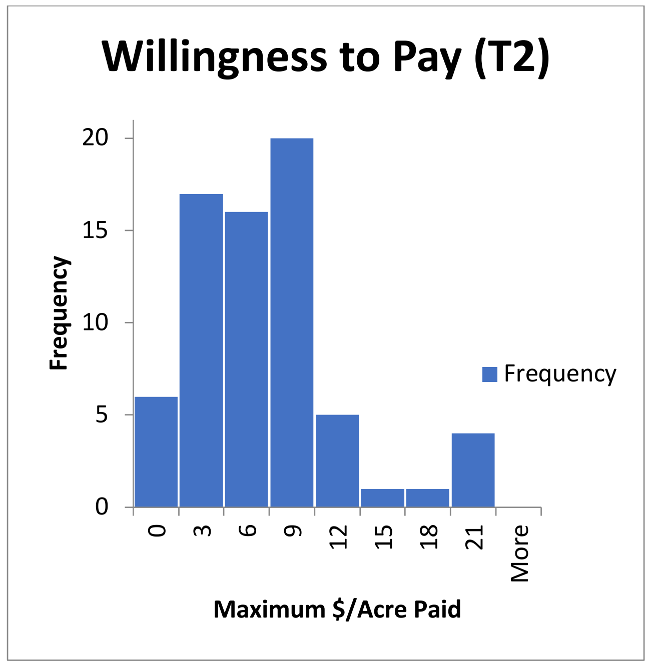


Figure 7.1: Distributions for 'Willingness to Pay' and 'Willingness to Accept'

Table 3 offers several descriptive statistics for each distribution. The first point to note is a sizable difference in means, with Treatment #1 (data owned by farmer) displaying a mean valuation of 11.6 ($11.6 per acre) versus a mean of only 7.0 ($7.0 per acre) for Treatment 2 (data owned by firm). The difference in medians between the two treatments was even greater, with Treatment 1 displaying a median of 12 versus a median of only 6 for Treatment 2. Both distributions skew positively, though Treatment 2 (1.09) skews considerably more than Treatment 1 (0.21). Despite these differences in mean and median, Treatments 1 and 2 share a mode of 9. As well, each treatment displayed a similar standard deviation (4.9 for Treatment 1 and 5.0 for Treatment 2). Finally, Treatment 1 showed thicker tails (with a kurtosis value of -0.41) while Treatment 2 was quite 'peaked' (with a kurtosis value of 1.09).

	Treatment #1	Treatment #2
n =	67	70
sum	753	504
mean	11.6	7.0
median	12	6
mode	9	9
SD	4.9	5.0
skewness	0.21	1.09
kurtosis	-0.41	1.44

Table 7.1: Descriptive Statistics for Treatment 1 and Treatment 2

Finally, an Anderson–Darling test for normality determined that the populations represented by neither Treatment 1 nor Treatment 2 could not be assumed to be normally-distributed. Visually, this is more obvious in the case of Treatment 2, whereas Treatment 1 bears some visual similarities to the ‘bell curve’ of a normal distribution. Determining that both samples were likely nonparametric was critically important in terms of the subsequent tests this study used to measure potential relationships between the relevant variables.

7.1.2 Analysis

Though the difference in means between Treatments 1 and 2 was evident, an explicit test was necessary to confirm the statistical significance of this difference. Because the distribution of results for each treatment was determined to be nonparametric, comparing the two means required a nonparametric test. The Unpaired Two-Samples Wilcoxon Test was determined to be appropriate for comparing the means of two samples from populations assumed to be dependent and nonparametric. The samples were considered dependent in that they were drawn from the same class of students, all of whom received the same briefing information.

The results of the Wilcoxen test, conducted using the statistical software R, determined that the difference in means between Treatments 1 and 2 was highly statistically-significant, displaying a p-value of 1.549e-06. Figure 9 provides a screenshot depicting the results of this test.

```
> wilcox.test(Treatment1, Treatment2, alternative = "two.sided")

        Wilcoxon rank sum test with continuity correction

data:  Treatment1 and Treatment2
W = 3442.5, p-value = 1.549e-06
alternative hypothesis: true location shift is not equal to 0
```

Table 7.2: Results of Two-Samples Wilcoxon Test

This study determined that an endowment effect would be recognized given a statistically significant difference between the means of Treatment 1 and Treatment 2. The above test verified an abundantly clear endowment effect, which resulted from the opposed starting positions (regarding ownership in ag-data) of each group. Given that the condition of ownership should have no impact on a rational actor's valuation of ag-data, this result contradicts the 'expected utility theory' of classical economics. In a population of n=137 comprised entirely of 'perfectly-rational actors,' there would be no expected difference in mean between respondents in Treatments 1 and 2. Without question, a statistically-significant difference in mean on the order of 56.1% constitutes clear evidence for the presence of the endowment effect. This result suggests that the pre-assignment property rights in ag-data, particularly if to producers, could impede Coasian bargaining, leading an *inefficient* (and also potentially *inequitable*) economic outcome.

7.2 SECONDARY ANALYSIS: WORLDVIEWS

7.2.1 Results

The secondary variable of interest in this study was the mix of worldviews held by agricultural producers. The questions in the third survey component were designed to measure the strength of a respondent's attachment to each of three worldviews (i.e. realist, liberal, critical). This was measured using a point system that assigned one point for each answer corresponding to a worldview. Figure 10 reveals the results of this measurement for respondents under Treatment 1, showing the frequency of respondents' accumulated scores for each worldview.

Each treatment group features a comparable distribution of points toward each worldview (i.e. on average, all 137 respondents were comparably attached to each worldview, regardless of which treatment they received in second survey component). In other words, the overall distribution of attachments to each worldview was (more or less) consistent across the entire sample set, which would be expected in that respondents were drawn from the sample class of students. Further, this consistency suggests that the overall survey design succeeded in avoiding ordering effects. This is to say that, as intended, neither Treatment 1 nor Treatment 2 appear to have biased respondents under each respective condition toward a particular set of worldview preferences. This is very important given that the experiment intended to investigate if respondents' worldviews—a set of personal characteristics understood to be independent of and prior to their decision-making in bargains (i.e. independent variable)—impacted their valuation of ag-data ownership (i.e. dependent variable) under each treatment.

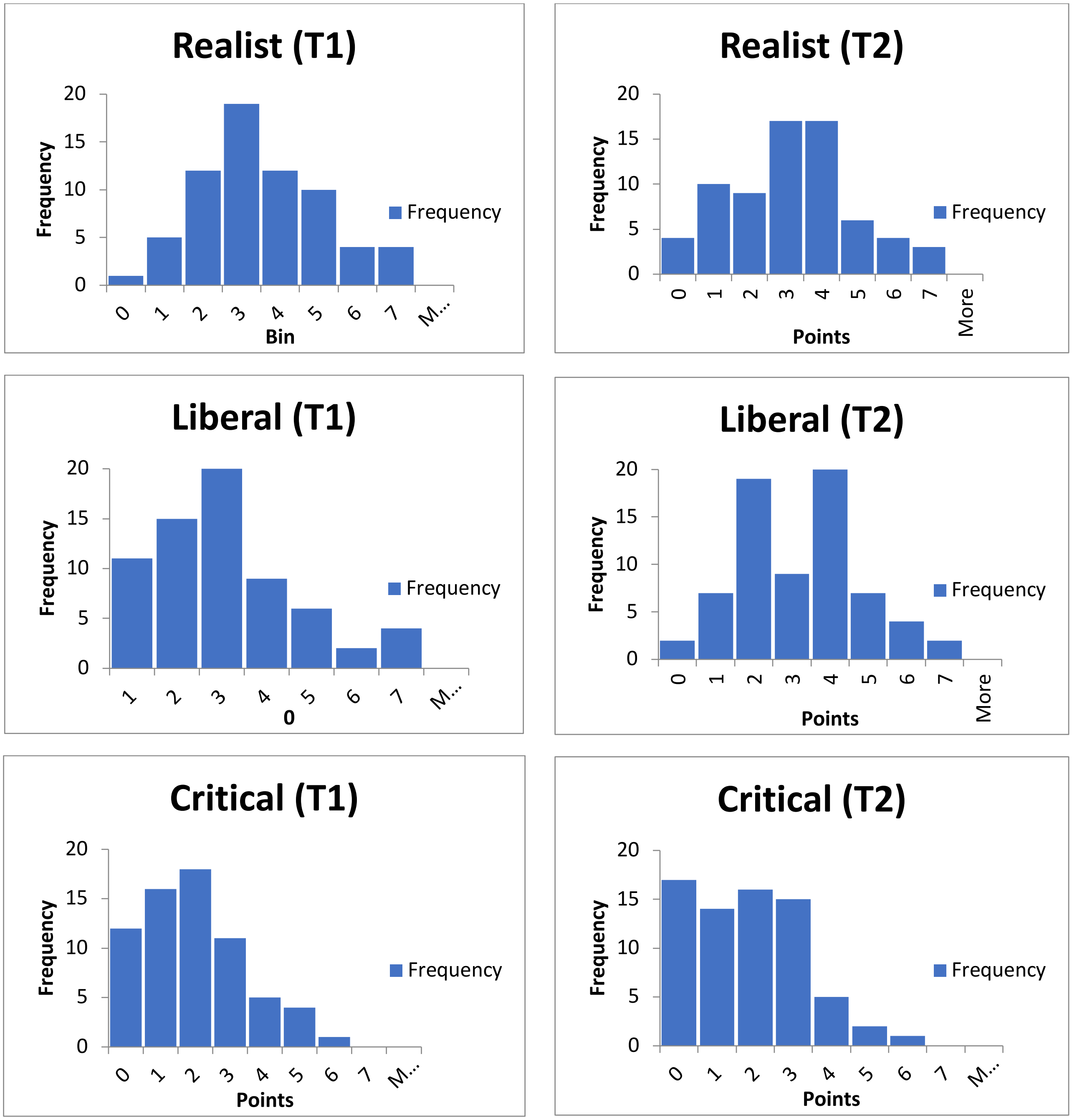


Figure 7.2: Distributions for Worldviews under Each Treatment

Table 4 provides a comparison of the mean scores for each worldview among respondents under Treatment 1 and Treatment 2. Under both treatments, respondents were, overall, most attached to the Realist worldview ($\mu = 3.52$ for T1; $\mu = 3.17$ for T2), but only slightly more than the Liberal worldview ($\mu = 3.06$ for T1; $\mu = 3.21$ for T2). Respondents under both treatments were considerably less attached to the Critical worldview ($\mu = 1.96$ for T1; $\mu = 1.81$ for T2).

Worldview	Means	
	Treatment 1	*Treatment 2*
Realist	3.52	3.17
Liberal	3.06	3.21
Critical	1.96	1.81

Table 7.3: Mean Worldview Scores For Both Treatments

Last, the same Anderson–Darling test for normality determined that the distributions for each worldview, under Treatments 1 and 2, could not be assumed to be normally distributed. Again, determining this was relevant to the subsequent analysis of potential relationships between respondents' worldview scores and their valuations for property in ag-data.

7.2.2 Analysis

The secondary analysis of this thesis was concerned with whether producers' attachment to a realist, liberal, or critical worldview impacted the valuation of ag-data. This was measured by testing for a statistically-significant relationship (positive or negative) between respondents' worldview scores and the price at which they valued ag-data. Comparing such potential relationships among respondents under Treatment 1 with those under Treatment 2 presented a way to examine how the worldviews of producers might attenuate the impact of the endowment effect—if the strength of their attachment to any of the three worldviews might amplify or lessen the dynamics of loss aversion (i.e. endowment effect) determined to be present in the prior primary analysis.

Because the distributions of all relevant variables were determined to be nonparametric, this analysis required a correlation test appropriate for nonparametric data. The Spearman's Rank-Order Correlation test (akin to a Pearson correlation but for nonparametric variables) was determined to be most appropriate given that—though nonparametric—the relevant variables were ordinal (all are, in fact, interval), and the relationship this test was interested in was monotonic but not necessarily linear. Unlike a regression, this test accounted for correlation but not the direction of a potential relationship between variables. Though admittedly inadequate to determine a potential causal (and, thus, directional) relationship between worldviews (i.e. independent variable) and producers' valuation of ag-data (i.e. dependent variable), the test was sufficient to establish if and to what degree any potential relationships exists between the relevant variables.

Six tests were conducted, using R, to explore potential correlation between **Variable 1**, respondents' valuations under both treatments, and **Variable 2**, their respective scores corresponding to each worldview (i.e. Realist, Liberal, and Critical). Table 5 displays the results of these tests. Under '**Variable 1**,' T1($) represents the valuation of respondents under Treatment 1 and T2($) represents those of respondents under Treatment 2;

‘**Variable 2**’ represents respondents’ overall scores corresponding to each respective worldview. **ρ** represents the Spearman’s correlation coefficient, which measures “the strength and direction of association between two ranked variables.”[146] Finally, ‘**p-value**’ signifies the statistical significance of the correlation between the **Variable 1** and **Variable 2**, while ‘**sig**’ represents which range of statistical significance each correlation falls within (* indicates a p-value < .10, ** a p-value < .5, and *** a p-value < .01).

Variable 1	Variable 2	ρ	p-value	sig
T1($)	Realist	0.1307	0.2919	
T1($)	Liberal	-0.1712	0.1659	
T1($)	Critical	-0.1521	0.2229	
T2($)	Realist	-0.2268	0.0590	*
T2($)	Liberal	-0.0281	0.8175	
T2($)	Critical	0.2044	0.0896	*

Table 7.4: Correlations between Worldview and Endowment Effect

As observed in Table 5, a low overall degree of statistical significance was found among the correlations tested. The most statistically-significant result was a negative correlation between ‘T2($)’ and ‘Realist,’ displaying a p-value (0.0590) just shy of the standard acceptable confidence level (0.05). The second result with any degree of significance was a positive correlation between ‘T2($)’ and ‘Critical’ (p-value = 0.0896). Ultimately, neither result was sufficiently sufficient to inform behavioural modelling or policy analysis in the subsequent chapter.

Though shy of the standard level of confidence necessary to reasonably assume a relationship between variables, the above results, nonetheless, provide some food for thought. Intriguingly, each of the two (somewhat) significant correlations involved T2($). One result suggests that the condition of non-ownership may differentially depress Realists ‘willingness to pay.’ One could extrapolate further that the endowment effect may be stronger among Realists; however, the corresponding correlation—though positive—between T1($) and Realist was not statistically significant, thus failing to demonstrate that Realists are differentially motivated by the framing of ‘domains of gain.’

The observed negative correlation between T2($) and Critical suggests that, contrary to Realists, the same condition of non-ownership (a ‘domain of loss’) may have less impact on the ‘willingness to pay’ of Criticalists. The inverse of the Realist case, one could extrapolate that the endowment effect may be weaker among Criticalists; however (as in the previous case), the corresponding correlation between T1($) and Critica’—though negative—was not statistically significant, thus failing to demonstrate that Criticalists are differentially unmotivated by ‘domains of gain.’

[146] “Spearman’s Rank-Order Correlation - A Guide to When to Use It, What It Does and What the Assumptions Are.”

Chapter VIII. BARGAINING MODELS

8.1 MODEL OVERVIEW

The results of the experiment revealed that the endowment effect may significantly impact producers' valuations of property rights in ag-data. This section examines the potential implications of the endowment effect as an impediment to Coasian bargaining and—by extension—to an *institutional* configuration whereby producers could share in the value generated through *off-farm* use. Where Chapter IV advanced the combination of producer ownership and ag-data markets as a viable *institution* to realize the policy goals of *efficiency* and *equity*, this chapter considers whether the knowledge gained through the behavioural experiment (i.e. the likely presence of the endowment effect) undermines this viability. Specifically, the concern is that, if producers are assigned ownership to ag-data, the endowment effect may cause them to overvalue their data such that they demand a price (i.e. their minimal valuation) higher than what an agribusiness is willing to pay (i.e. their maximum valuation). In this scenario, many producers would retain exclusive ownership of much of the newly-generated ag-data, thereby excluding agribusinesses from using it in positive-sum use-cases that generate new economic value and align with the public interest. Similarly, producers withholding data could hinder agribusiness having a sufficient volume of data to unlock the utility of 'big data,' which would be positive in the case of *secondary use*, but negative in the case of *tertiary use*. This chapter introduces a simple model, incorporating a handful of assumptions and flexible parameters, to test whether the endowment effect could impede Coasian bargaining.

8.2 MODEL PARAMETERS

8.2.1 Source of Valuation for Agribusiness vs. Producer

The model features two actors: the producer and the agribusiness. Each is meant represent the aggregate of producers and agribusinesses, respectively. This simplification is reasonable in that the distribution of benefits from *primary*, *secondary*, and *tertiary* use, in each case, accrue consistently to the aggregate of producers and/or to the aggregate of agribusinesses. Under this simplified model, the relevant question is how each aggregate actor determines their respective valuation of ag-data before entering the bargain.

For reference, Figure 11 depicts the same *institutional* structure introduced as a viable policy solution in Chapter IV. Its underlying logic of Coasian bargaining is that, in a successful market, what determines the 'clearing price' for market allocation is the value of the traded item to the actor who values it more. This should be the agribusiness, who can use ag-data to generate value through *off-farm* use in ways a producer cannot; thus, the agribusiness valuation is determined by the 'utility' of the use-cases they can avail. Agribusinesses, as the practitioners of *secondary* and *tertiary* ag-data use, are much better equipped to value ag-data in terms of its benefits to them; it is reasonable to assume that agribusinesses are motivated to collect and control ag-data by the real or prospective value it could generate for them through *off-farm* use-cases and, further, that they have likely attempted to calculate that value (i.e. the maximum price they would be willing to pay) and factor this calculation into their decisions in bargaining. The challenge is that the producer lacks the ability to accurately appraise the utility or disutility associated with ag-data ownership.

Institutions (Property Rights) ↓	Technology (Capacity) ↓
Ownership ↓	Utility ↓
Starting Position (seller or buyer) ↓	Valuation ↓
Ag-data Markets ↓	
Use-cases ↓	
Distribution of Benefits and Costs	

Figure 8.1: Ag-Data Markets

How producers determine the value of ag-data is a more difficult question. At a time when much about the digitization of agriculture and agri-food production remains highly uncertain, producers are in a poor position not only to capture value *off-farm* but also to understand the potential outcomes of *off-farm* use. While producers may be aware of some risks attached to *secondary use,* they are less able to quantify those risks than agribusinesses (who are on the upside of *secondary use* and, thus, value it positively). Producers are, likewise, in a poor informational position to determine the value of *tertiary use*, leaving them less aware of its value to agribusinesses. Given this state of information asymmetry, the 'starting point' of producer valuation can have a major impact.

While this 'starting point' problem complicates the goal of modelling producer valuation, the experiment revealed a robust 'endowment effect.' The endowment effect is not a feature of the (uncertain) economic environment, but rather consists in the structure of the human mind, which behavioural economics shows is often susceptible to systematic errors.[147] Such errors by producers are all the more likely given the dearth of information available to them about the risks associated with *secondary* ag-data use (for producers, withholding ag-data is worth the protection from *secondary* exploitation it provides) as well as the potential

[147] Kahneman, *Thinking, Fast and Slow*.

value of ag-data to agribusinesses related to *tertiary* use (which producers could share in via bargaining). Thus, the endowment effect suggests that, regardless of the reasonable 'starting point' for producer valuation, producers are likely to value ag-data more if they own it and less if they do not. Table 6 depicts the sources of valuation for each actor (i.e. producer and agribusiness) tied to *primary*, *secondary*, and *tertiary* use, which are the basis by which the model operates to predict bargaining outcomes.

	Agribusiness	Producer
Primary	Profits from the sale of precision agriculture products	Productivity/efficiency: higher yields/quality; lower costs
Secondary	Gaining value from producer	Avoiding value loss
Tertiary	Positive-sum *off-farm* use-cases	

Table 8.1: Source of Valuation for Each Actor

8.2.2 Payoffs for Primary, Secondary & Tertiary Use

This model reintroduces the important concepts of Primary, Secondary, and Tertiary ag-data use. The model considers the marginal benefit (using an arbitrary unit) of *primary*, *secondary*, and *tertiary* ag-data use to each actor:

- *Primary use* (e.g. precision agriculture) is positive-sum and generates +10 marginal benefit for the producer and +10 for the agribusiness. *Primary use* will occur regardless of whether the initial allocation of property rights in ag-data because it is the very process the drives ag-data generation.
- *Secondary use* (e.g. commodity speculation) is zero-sum and transfers 10 marginal benefit from the producer to the agribusiness: +10 marginal benefit or the agribusiness and -10 for the producer. Commodity speculation is the most likely use-case falling into the secondary use category. *Secondary use* occurs only if agribusinesses own ag-data (either by pre-assignment or through Coasian bargaining).
- *Tertiary use* (e.g. product innovation, etc.) is positive-sum and generates +10 marginal benefit for the agribusiness and at worst 0 for the producer. This category includes various use-cases whereby agribusiness firms generate new value without any loss to the producer (e.g. targeted marketing, product and end-user design, supply chain and logistics management, risk mitigation, and improved traceability and sustainability). As above, *tertiary value* occurs only if agribusinesses own ag-data.

8.4 THE MODELS

8.4.1 First Model: Agribusiness Valuation > Producer Valuation

Figure 12 depicts the potential outcomes of Coasian bargaining under the assumption that (1) the agribusiness values ag-data more than the producer and (2) no endowment effect is present. Assigning property rights to the agribusiness results in 30 marginal benefit for the agribusiness and 0 for the producer. This occurs because the producer, who values the ag-data at 10, is unwilling to pay more than 10 to acquire ownership (far below the minimum of 20 agribusiness would be willing to accept). On the other hand, assigning property rights to the producer results in 15 marginal benefit for the producer and 15 for the agribusiness. This result occurs because the agribusiness, who values ag-data at 20, is willing to pay the producer more than 10 to acquire ownership (it is assumed they strike a bargain half-way between 10 and 20: 15). This '15 and 15' payoff is as efficient as the '30 and 0' but superior in terms of *equity*, and is, thus, the optimal outcome.

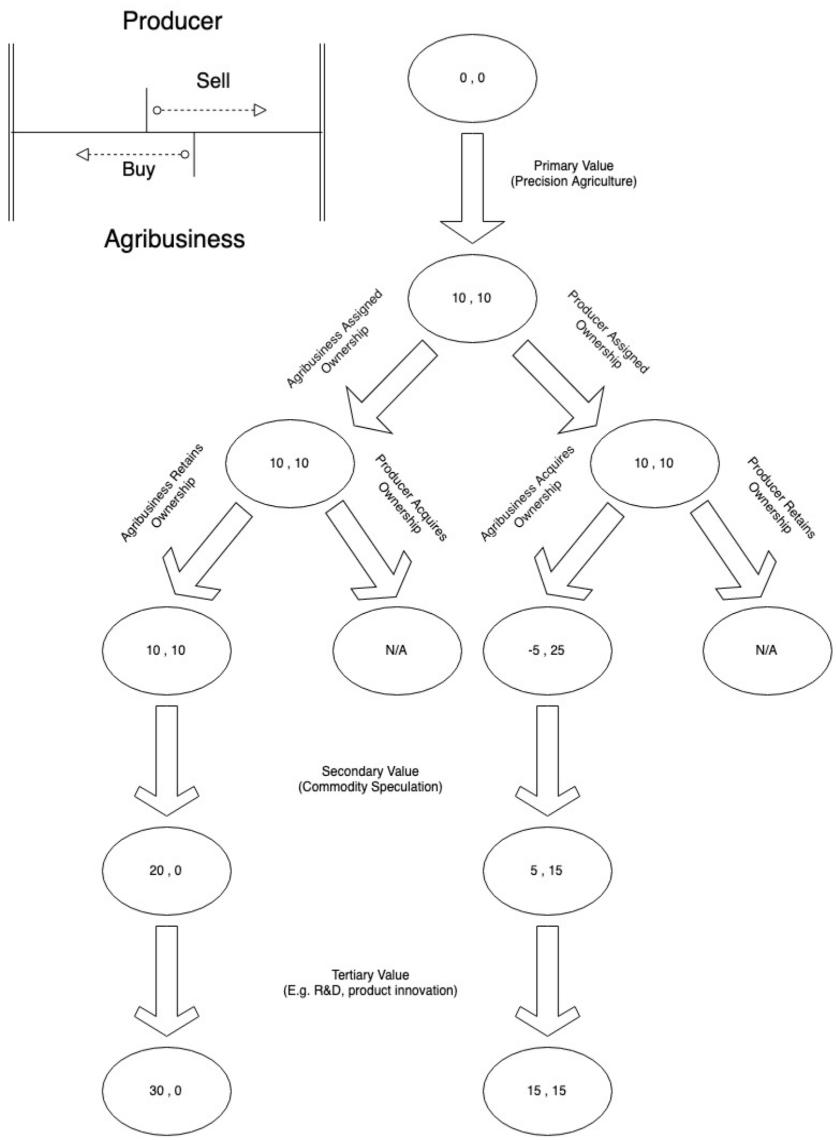


Figure 8.2: First Model - Agribusiness Valuation > Producer Valuation

8.4.2 Second Model: Producer Valuation > Agribusiness Valuation

Figure 13 depicts the potential outcomes of Coasian bargaining under the assumption that the producer (irrationally) values ag-data more than the agribusiness and no endowment effect is present. In this case, assigning property rights to the agribusiness results in the worst possible outcomes for the producer (-10) but 30 marginal benefit for the agribusiness. This is a poor outcome both in terms of *efficiency* because only 20 (rather than 30) net value is added to the economy; the outcome is poor in terms of *equity* because the producer is left with a negative marginal benefit. On the other hand, assigning property rights to the producer results in a marginal benefit of only 10 for the producer and 10 for the agribusiness. This outcome, which occurs because the producer is (irrationally) unwilling to sell property rights to the agribusiness (not even for a price of up to 10), is *equitable* but *inefficient*. This demonstrates the negative impact (in terms of both *efficiency* and *equity*) resulting from overvaluation by the producer, which—though it protects the producer from *secondary* exploitation—also prevents the agribusiness from adding new value to the economy through *tertiary use*.

Figure 13: Second Model – Producer Valuation > Agribusiness Valuation

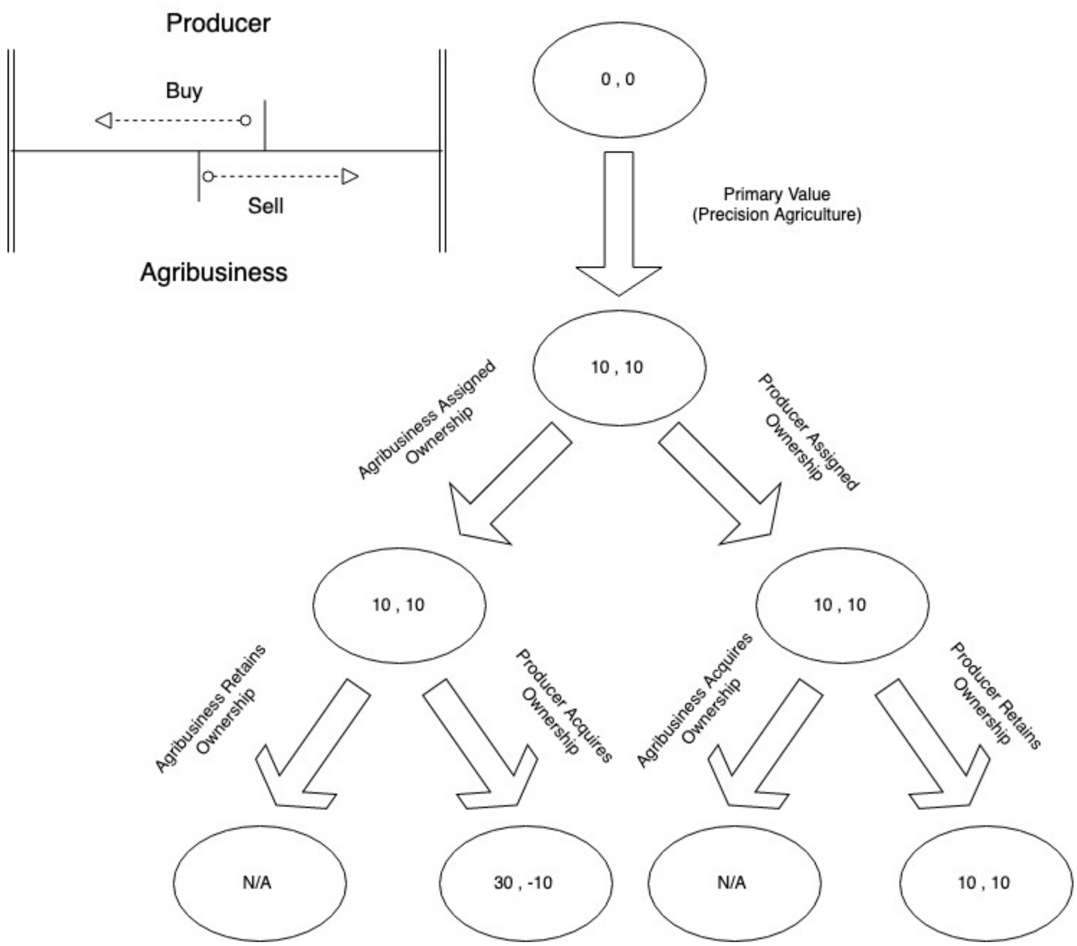


Figure 8.3: Second Model - Producer Valuation > Agribusiness Valuation

8.4.3 Third Model: Endowment Effect

Figure 14 depicts virtually the same Coasian bargaining scenario as in Figure 1, but with the endowment effect in play. Whereas the producer had previously valued ag-data at a price lower than 20 (its value to the agribusiness), the endowment effect now pushes the producer's valuation (under the condition of ownership) above 20. This cancels the possibility of a bargain whereby the agribusiness purchases ownership at a price between 10 and 20 (the cost to the agribusiness is more than offset through the value generated by a combination of *secondary* and *tertiary* use), effectively nullifying Coasian bargaining.

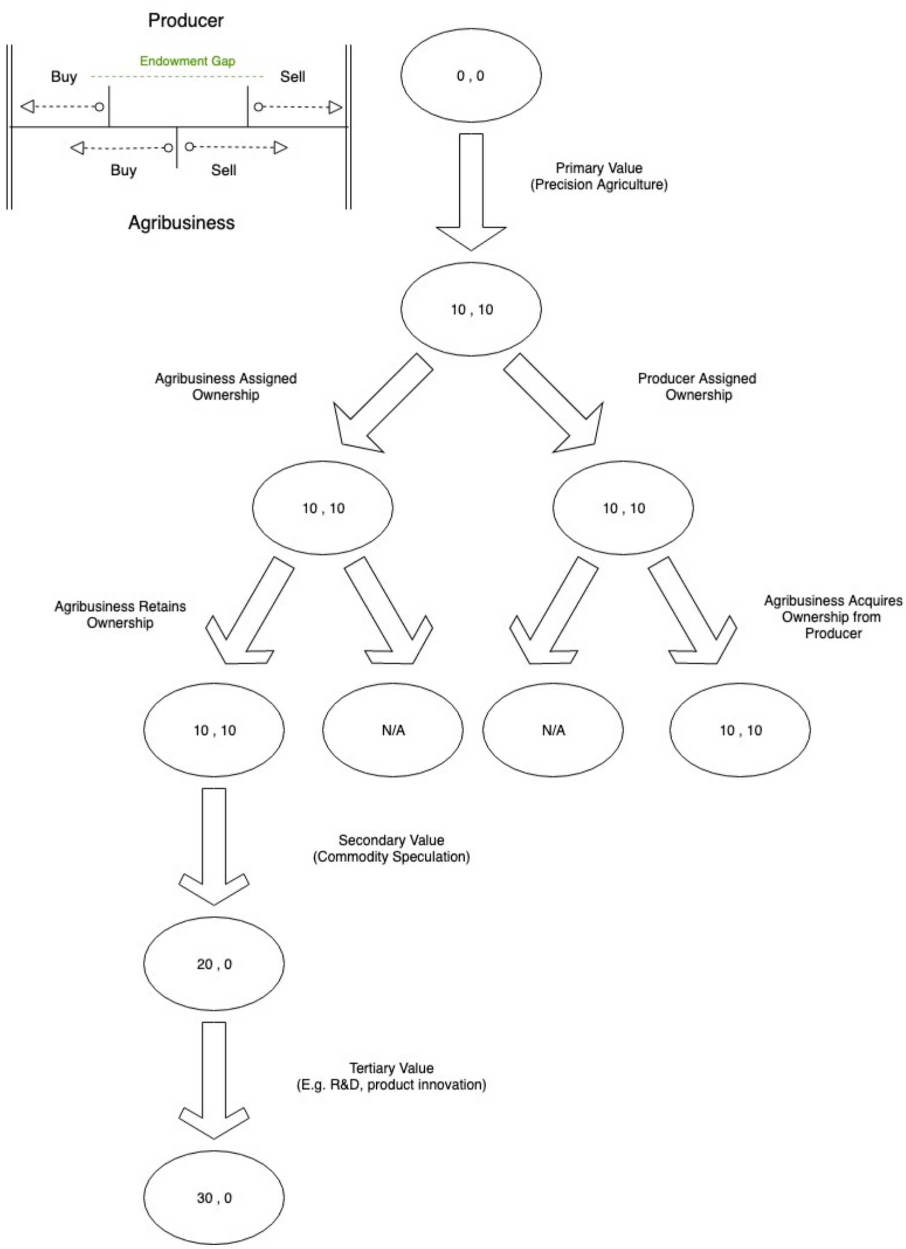


Figure 8.4: Third Model - The Endowment Effect

CHAPTER IX. POLICY IMPLICATIONS

9.1 OVERVIEW

For stakeholders in the Canadian agri-food system to realize the full potential and share in the benefits of digital innovation, ag-data must be freely shared and transacted in a stable, predictable, and trustworthy environment. Fundamentally, the value of ag-data is determined by its utility—i.e. how the user can leverage it to capture value (or in terms of how retaining ownership could prevent value-loss). In these early days of technological development, producers (and potentially agribusinesses) have insufficient information to accurately value a property interest in ag-data. Inherently, this hinders early efforts by policymakers to assess the viability of ag-data markets as an *efficient* and *equitable* institutional framework for allocating rights in ag-data.

As demonstrated in Chapter VIII, the results of the behavioural experiment show that agricultural producers will value ag-data more as owners; however, understanding this does not shed much light on where the range of producers' valuations falls relative to agribusinesses. For that matter, given that most relevant use-cases for ag-data are not yet developed or implemented, it is too soon to develop a clear sense of where agribusinesses value ag-data—whether now or in the future as use-cases develop and their impacts become better understood. Indeed, the reality is that the actual monetary value of ag-data (current and future) is likely unknowable at this stage. Nevertheless, for policy to take a proactive role in shaping the digitization of agriculture, the time is now. This chapter considers ag-data markets as an alternative to the status quo, while recognizing potential impediments to this *institutional* configuration. This final chapter offers further suggestion on a way forward.

9.2 REVISITING THE 'TALE OF TWO FUTURES'

Before further discussing the opportunities and challenges surrounding ag-data markets, it bears recalling why the status quo is likely misaligned with the public interest. Again, the US poultry market provides an instructive case study for understanding the perils of over-concentrated market power and, particularly, the potential for data to exacerbate equity. *The Meat Racket* by Christopher Leonard portrays a broken food system, where the "95 percent of Americans [who] eat chicken" are all but forced "to support a system that keeps farmers in a state of indebted servitude, living like modern-day sharecroppers on the ragged edge of bankruptcy."[148] He argues that "[this] system extracts its costs from consumers as well" in that this oligopoly has "[raised] prices more and more in recent years, even as the wages of U.S. households have stagnated."[149]

[148] Leonard, *The Meat Racket*.
[149] Leonard.

In recent years, data appear to have played in insidious role in this process of centralization. A string of class-action lawsuits filed by chicken producers, food retailers, and restaurants all allege that since 2008 the 'big chicken' oligopoly,[150] which controls 95% of the $30-billion broiler chicken market in the U.S., have "engaged in a price-fixing conspiracy through use of a third-party database software called Agri Stats."[151] Because this database allegedly collects 95% of poultry production data on 22 million chickens each day, major chicken processors can access production data covering nearly the entire industry. This facilitates a form of indirect collusion to coordinate production volumes and artificially fix the price retailers pay for poultry, ultimately harming both retail operators and consumers. One lawsuit noted, "The consequence of [poultry companies' coordinated production] cuts in 2008 and 2011-2012 has been a nearly 50% increase in Broiler [chicken] wholesale prices by one measure since 2008, despite input costs (primarily corn and soybeans) falling roughly 20% to 23% over the same time period."[152] Together, this combination of unchecked vertical integration and market power, anticompetitive collusion through mass data consolidation, and the zero-sum 'tournament system' by which poultry companies determine the prices paid to contract chicken producers, has all but obliterated "the broad-based network of small businesses that were once the backbone of rural America" and "[extracted] savings from the farmer without passing them on to the consumer."[153]

This situation provides an analogue to what would be considered *secondary use* in the crop agriculture context. Though the case of US poultry is by no means predictive of ongoing trends in the digitization of crop agriculture, it raises relevant concerns regarding the risks of over-concentration of control over data. A recent think-piece from Future Agenda points out that, "[i]n a world of increasing inequality… the data ownership debate is polarised precisely because it is part of an already polarised political debate around… how the economic benefits of data collection and monetisation are distributed between the collectors and the collectees."[154] The vulnerability of crop producers is particularly concerning and, therefore, policy should focus on mitigating the potential risks from *secondary use*, while promoting opportunities for producers to share in the value created through *tertiary use*. If this could be achieved through policy without 'chocking off' innovation and impeding positive-sum *off-farm* use-cases, the *value chain transformation* stands to propel agriculture in a more utopian direction defined by greater abundance, technological progress, positive-sum dynamics, and an *equitable* distribution of benefits.

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[150] Tyson Foods, Perdue Farms, Pilgrim's Pride, Koch Farms, Sanderson Farms and others.
[151] Douglas, "Big Food Versus Big Chicken."
[152] Broiler Chicken Antitrust Litigation.
[153] Leonard, *The Meat Racket*.
[154] "Future Value of Data."

9.3 ARE MARKETS THE RIGHT MECHANISM?

Chapter IV determined that the *institutional* status quo, wherein agribusinesses collect and control all ag-data, is not aligned with the public interest. Specifically, the prospect of *secondary use* raises concern that agribusinesses could leverage ag-data to capture value at the expense of producers. To prevent zero-sum transfers of value from producers to agribusinesses (i.e. *secondary use*)—and provide producers with greater access to the positive-sum benefits of *tertiary use*—assigning a property interest in ag-data to producers was deemed the necessary precondition to *institutional* success. The aspiration was that property rights would allow for the emergence of ag-data markets whereby producers could capture a portion of the value created by *off-farm use* and exercise a degree of control over the data they produced.

This rationale derives from classical economic theory, which holds that, given clear delineation of property rights and sufficiently low transaction costs, bargaining will efficiently allocate use rights to the actor with the capacity to generate the most economic value through their use.[155] The logic of ag-data markets rests on the assumption that agribusinesses can generate more value from ownership than individual producers and, thus, would be willing to purchase use rights at a mutually-acceptable (i.e. 'market clearing') price. However, this assumes that both actors are able to accurately value ag-data in terms its respective opportunities and risks. Agribusinesses are far better equipped to value ag-data than producers, first, because they have access to it in aggregate and, second, because they have the greater knowledge, resources, and capacity. Thus, significant danger looms in the possibility that, due to behavioural dynamics, producers may enter the bargain overly valuing ag-data relative to agribusinesses , forestalling *efficient market exchange*. The outcome of this configuration would be *equitable,* in that producers would use their ownership rights to circumvent potential losses from *secondary use*; however, the concomitant drawback comes in terms of *efficiency*—the market would fail to *efficiently* allocate rights in ag-data, with the attendant opportunity cost of foregone positive sum *tertiary uses*.

As explored in the 'Third Model' in Chapter VIII, the endowment effect significantly increases the likelihood that any producer's valuation will be higher than that of an agribusiness, thereby precluding "mutually acceptable trades."[156] Moreover, this likelihood only increases as *off-farm* use-cases develop: though many producers may currently care little about if or how an agribusiness leverages their data, in time, their valuation of ag-data will likely increase considerably in proportion to their growing awareness of the risks (i.e. *secondary* exploitation) and opportunities (i.e. capturing 'their' share of *tertiary value)* associated with ownership. Adding to this dynamic, the endowment effect itself may become more pronounced when higher stakes are attached to ownership. Experts have suggested "that the [agribusiness] sees no value in a single

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155 Coase, "The Problem of Social Cost."

156 Kahneman, Knetsch, and Thaler, "Experimental Tests of the Endowment Effect and the Coase Theorem."

farm's data" to the extent that its impact on a large, aggregated dataset is negligible.[157] Functioning together, these dynamics present a significant risk of undermining the intended function of ag-data markets, negating not only the drawbacks, but also value of *off-farm* ag-data use. This strongly suggests that policymakers may need to consider alternatives beyond simple markets.

9.4 POTENTIAL POLICY DIRECTIONS

This section turns immediately to the question of which alternative *institutional* configurations could help overcome the deficiencies of simple ag-data markets. The crux of the issue is that assigning a property interest in ag-data to producers (for exchange), if simple markets are the venue for exchange, may fail to accomplish policy goals with respect to both *efficiency* and *equity*. The rational actor assumptions of classical economics likely do not hold in an environment where use-cases for ag-data have yet to develop and large asymmetries in information, capacity, and bargaining power exist between producers and agribusinesses. In lieu of more complete information about the opportunities and risks they face, producers default to less rational modes of decision-making. To address this issue, three additional institutional features have been identified to create the conditions necessary to circumvent *secondary use* as well as facilitate *tertiary use* and distribute its benefits among producers and agribusinesses.

It is worth noting that the potential value producers could obtain through selling their ag-data is significant. For example, even increasing a producer's profit per acre by an average of \$10 on a 50,000-acre operation adds \$500,000 to overall farm receipts. Given the increasing scale of today's farms, there is a clear economic case for ag-data as an additional revenue stream for producers. Provided the right institutional configuration, in theory producers stand to capture a significant portion of the considerable value generated through eventual *off-farm* use cases, a gain that could potentially exceed \$10 per acre. To this end, the following institutional features provide a few potential pathways to a more *equitable* distribution of the value from ag-data innovation.

9.4.1 Transparency

Information asymmetry drastically limits the ability of producers to accurately value ag-data in terms of its opportunities and risks. Bargaining from a position of ownership, producers would have control over their ag-data but still lack the information to judge when it is worth relinquishing control for monetary compensation. Producers would be less likely to overvalue ag-data rights (and might engage more *efficiently* in bargaining) had they the capacity to assess the relative magnitude of opportunities and risks associated with ag-data ownership.

157 Ellixson and Griffin, "Farm Data."

The 'transparency issue' has received considerable attention in a range of ag-data proposals and initiatives. While these efforts have certainly improved the degree of transparency demanded by more producers and guaranteed by agribusinesses, there is a long way yet to go. Most ag-data contracts today—whether in the U.S., Australia, or Canada—lack any provisions that, first, recognize a property interest in ag-data for producers and, second, require agribusinesses to reveal how they will use ag-data *off-farm* (i.e. transparency).

In 2014, the American Farm Bureau established the Privacy and Security Principles for Farm Data Ag Data (The Principles), setting out 13 broad principles [158] to inform contractual agreements between agribusinesses and producers regarding ag-data use. One among the 13, *Transparency and Consistency* connotes that:

> *"ATPs shall notify farmers about the purposes for which they collect and use farm data. They should provide information about how farmers can contact the ATP with any inquiries or complaints, the types of third parties to which they disclose the data and the choices the ATP offers for limiting its use and disclosure. An ATP's principles, policies and practices should be transparent and fully consistent with the terms and conditions in their legal contracts. An ATP will not change the customer's contract without his or her agreement."*

To further advance the adoption of the 13 principles by agribusinesses, a non-profit called the Ag Data Transparency Evaluator (ADTE) formed in 2018 to create the governing body responsible for administering the AgData Transparent Seal (the Seal), "a designation that demonstrates to customers and others that they are transparent in how they collect, use, store and analyze farmers' data."[159] Several notable agribusinesses[160] have received the Seal, John Deere being the first major player[161] and FCC the first Canadian company."[162] To obtain the Seal, an agribusiness must complete a questionnaire detailing their ag-data practices and provide sufficient evidence that: contracts with users clearly delineate ownership in ag-data to producers, *off-farm use* occurs only with the express consent of producers, and that complete transparency is maintained regarding the nature and outcomes of any *off-farm* ag-data activities.

The current list of signatories signals a positive trend in terms of greater control over ag-data on the part of producers; however, thought leaders in the ag-data space (including Todd Janzen, a central architect of the ADTE) have voiced concern that the status quo is not shifting fast enough: "ag tech providers still do not

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[158] 13 Principles: Education; Ownership; Collection, Access and Control; Notice; Transparency and Consistency; Choice; Portability; Terms and Definitions; Disclosure, Use and Sale Limitation; Data Retention and Availability; Contract Termination; Unlawful or Anti-Competitive Activities; Liability & Security Safeguards.

[159] Harris, "Building a More Efficient Road Map for Agricultural Data."

[160] AGCO, Ag Connections, Agrible, American Farm Bureau Federation, American Soybean Association, Beck's Hybrids, Conservis, CNH Industrial, Crop IMS, Dow AgroSciences, DuPont Pioneer, Farm Dog, Farmobile, Granular, Grower Information Services Cooperative, GROWMARK, Independent Data Management, John Deere, National Association of Wheat Growers, National Corn Growers Association, National Farmers Union, National Sorghum Producers, and The Climate Corporation

[161] Janzen, "The Ag Data Transparency Evaluator."

[162] Harris, "Building a More Efficient Road Map for Agricultural Data."

get it—ag data is not just 1s and 0s, but proprietary information that should be grounded in an ownership principle."[163] Indeed, the reality is that most agribusinesses have yet to embrace some or any of the 13 principles in their contractual arrangements with producers. While it is not clear that convincing agribusinesses to agree, on voluntarily basis, to provide transparency for their customers will enable effective ag-data markets, the ADTE have certainly made some headway (particularly given the involvement of a major player in John Deere) and the Seal has likely been (and will likely continue to be) a critical tool for educating producers about ag-data ownership and the opportunities and risk associated with *off-farm* ag-data use.

9.4.2 Data Licensing

De Beer notes that "the most basic element of property ownership is the exclusive right to control the terms and conditions of access to a resource."[164] In many ways, excludability is the most fundamental right attached to ownership in that it empowers the owner to preclude others from using the item in which property rights are held. In the agriculture and agri-food context, ownership in ag-data would empower producers to circumvent the risks of *secondary use* while ensuring that *tertiary use* occurs only with their permission and that they are able to share in the new value generated.

Before accounting for the impact of the endowment effect and other behavioural dynamics, simple ag-data markets were considered as a potential institutional path toward these benefits. However, too narrow a definition of excludability may limit the effectiveness of property rights as an *institutional* mechanism. Simple ag-data markets are likely too rigid—treating ownership as a strict binary and the act of transferring ownership as unidirectional, total, and permanent may be a problem.

Data licensing offers an alternative to the outright 'sale' of ag-data. It would allow producers to permit an agribusiness to use a particular dataset, in the context of a particular use-case, for a particular period. Inasmuch as the 'domain of loss' framing would have less impact on a producer's decision to *license* versus to *sell*, the endowment effect is likely far less present (if it exists at all) in a producer's decision of whether to license. If so, producers could simply license *their* ag-data (which would remain *their*s) to agribusinesses for particular use-cases rather than face the decision to permanently bargain away ownership. Another major advantage lies in that fact that agribusinesses would need to specify, as a necessary step of negotiating any licensing agreement, the particular use-case(s) to which the license would apply, thereby helping to alleviate many of the transparency concerns discussed above. Finally, data licensing could provide a source of recurring income for producers, whereas, under a simple ag-data market, producers would be able to sell each set of particular data only once.

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[163] Janzen, "Ag Data Ownership."
[164] de Beer, "Ownership of Open Data: Governance Options for Agriculture and Nutrition."

9.4.3 Data Co-ops & 'Datatrusts'

The volume of data produced on an individual farm is infinitesimally small relative to the troves of aggregated ag-data controlled by ATPs. This concentration of ag-data and market power is problematic for several reasons, two of which apply specifically to ag-data exchange. As noted, overconcentration of ag-data could undermine the *efficiency* of simple markets in that the position of agribusinesses may leave them unwilling to pay the minimum sum demanded by producers for ag-data from their individual farm. Ellixson and Griffin note that "farmers have no bargaining power once the data system [reaches] a critical mass of farms/acreage" [165] because "data is worth more when there is more of it." [166] This not only contributes to the likelihood of producers valuing ag-data more than agribusinesses (i.e. *inefficient*), but also lowers the benefit producers would receive from transacting in ag-data markets (i.e. *inequitable*).

One *institutional* measure that could address these problems is the establishment of data co-operatives (co-ops), whereby "a group of farmers may have a better chance at recovery considering their collective data has more value" [167] than that of an individual producer in the same negotiation. Co-ops could create countervailing market power that could advance the policy objectives of *efficiency* and *equity*, particularly in conjunction with the use of data licensing agreements. The policy window to support and encourage such developments may narrow with greater consolidation, but for now is fairly wide open in that the field of ATPs remains competitive and varied.[168] Greater consolidation among ATPs would increase the volume of ag-data that producer co-ops would need to aggregate to exert market power. Therefore, the sooner producers coordinate in such ways to improve their market position vis-à-vis data, the better.

A handful of initiatives are underway to consolidate producer-owned ag-data for a variety of purposes other than those proposed above (i.e. increasing their value when monetized). These initiatives align with the concept of a 'datatrust,' which "establishes a technology framework that enables the control and sovereignty of data assets between trusted data partners."[169] One such group is the Agricultural Data Coalition (ADC),[170] with the stated mission "to create a neutral, independent, farmer-centric data repository where farmers can securely store and control the information collected by technology tools."[171] A similar initiative is the Global Open Data for Agriculture and Nutrition (GODAN), which is mandated to make "agricultural and nutritional data available, accessible, and usable for unrestricted use worldwide."[172] These initiatives, and others, could help

[165] Ellixson and Griffin, "Farm Data."
[166] Begemann, "DataStore Means Farmers Can Sell Data For Real Dollars."
[167] Ellixson and Griffin, "Farm Data."
[168] Ellixson and Griffin.
[169] "Data Ownership in a World of Big Data."
[170] Agricultural Data Coalition, "Ag Data Coalition: Putting Farmers in the Driver's Seat."
[171] Archer and Delgadillo, "Key Data Ownership, Privacy and Protection Issues and Strategies for the International Precision Agriculture Industry."
[172] "Open Data."

build a new set of producer-led entitles with the express purpose of aggregating ag-data to increase its monetized value through sale or licensing agreements. The result should be accelerated innovation, more profitable and sustainable production and a more secure food supply.

9.5 DISCUSSION

Each of the three aforementioned policy measures addresses a particular defect one could reasonably foresee impeding the success of simple ag-data markets. However, the positive impacts of each policy measure would work to reinforce one another. An *institutional* framework that (1) required contracts between agribusinesses and producers to adhere to the ADTE's 13 principles (particularly *Transparency and Consistency*), (2) enabled producers to *license* (instead of *sell*) ag-data in a transparent and trustworthy environment, and (3) featured producer-controlled data institutions (co-ops and/or datatrusts), could meet all the necessary conditions for an ag-data market that provides a sufficient degree of control for producers while still allocating ag-data toward the most productive use-cases. It falls beyond the scope of this thesis to specify how, under Canadian law, to legislate or govern such an institutional framework into existence. Rather, this thesis first considered the behavioural dynamics potentially threatening the *efficiency* of simple ag-data markets, then offered—in broad strokes—three very general *institutional* mechanisms that could, together, circumvent these behavioural dynamics. Such an *institutional* configuration would—as set out as broad policy objectives in Chapter I—support innovation and *efficiency*, promote greater trust and predictability, and allocate property rights such that ag-data permeates existing industrial systems in ways that generate positive-sum outcomes that benefit all stakeholders.

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APPENDICES

APPENDIX A. CONSENT FORM

Graeme Jobe
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We are interested in learning about your perceptions and responses toward data, risks and opportunities. These responses will help researchers at the University of Saskatchewan to gain insight into the market interactions between farmers and large agribusiness firms. We invite you to share your responses!

This 30-minute survey, funded by SSHRC, is hosted by Voxco, a Canadian-owned and managed company whose data is securely stored in Canada.

This research project has been approved on ethical grounds by the University of Saskatchewan Research Ethics Board, and has indicated that there are no foreseeable risks. Any questions regarding your rights as a participant may be addressed to that committee through the Research Ethics Office ethics.office@usask.ca; (306) 966-2975. Out of town participants may call toll free (888) 966-2975.

In order to complete this survey, you may be required to answer certain questions; however, you are never obligated to respond and you may withdraw from the survey at any time by closing your internet browser and notifying the research administrator. Participation is strictly voluntary.

By selecting next and completing this questionnaire, your free and informed consent is implied and indicates that you understand the above conditions to participate in this study.

Please consider printing this page for your records.

APPENDIX B: DEBRIEFING MESSAGE

Thank you for your participation in this survey. The purpose of this survey was to determine whether farmers are likely to place a higher value on data rights if they already have ownership. In other words, will farmers pay less to acquire ownership than what they would accept to sell these rights? This is what is referred to in behavioural economics as the 'endowment effect.' Our prediction is that the endowment effect will be present in farmers' valuation of data ownership rights. Your participation helps us to learn and understand how farmers interact with agribusiness firms, which provides tremendous insight into how digital technology will impact the agriculture sector—both in Canada and abroad.

If you have any questions about the survey or would like to receive a summary of the research results, please contact Graeme Jobe (gjj397@mail.usask.ca), Graduate Student or Dr. Peter Phillips (peter.phillips@usask.ca), Supervisor at the University of Saskatchewan.

We sincerely thank you for your time and your help!