Governing Value Chain Disruption in Agriculture and Agri-foods:

A Behavioural Approach to Assessing Policy Implications

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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—holds a great deal of valuable information about the global food supply, present and future.[2] As digital hardware and software rapidly introgress agricultural production systems,[3] an on-farm transformation in productivity and efficiency is creating the conditions for an impending value chain transformation driven by ag-data. The on-farm transformation benefits both producers and agribusinesses,[4] but the broader value-chain transformation may carry a significant risk of value migrating from producers to large agribusinesses. Though still on the horizon, policymakers should pay close attention to how this future unfolds and consider the role of policy in promoting the ideal conditions for growth, innovation, and mutual benefit among stakeholders.[5]

Unclear are the definite forms this value chain disruption will take, the stages of its unfolding, and—to some extent—which resulting opportunities or risks will face whom. Though the scope and timing remain uncertain, policymakers must confront this transformation proactively and strive to understand more about a variety of questions: How will various stakeholders leverage ag-data, to what consequences, and who wins and loses? Who will own ag-data and what rights should ownership confer? Under what rules and conditions will ag-data be valuated and exchanged? And, finally, what is government's role? Of the many unresolved questions, the first concerns how agribusinesses will leverage ag-data to capture new and existing value across the value chain. This is the 'why' driving the emergence of new industrial

[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."

structures that will determine how various stakeholders control, valuate, and exchange ag-data in the digital future of agriculture and agri-foods.

Currently, there are several potential *off-farm* use cases for ag-data, which could facilitate innovation in targeted marketing, product and end-user design, supply chain and logistics management, risk mitigation, and improved traceability and sustainability. Ostensibly, all the above would promote positive-sum outcomes, even if agribusinesses rather than producers capture the lion's share of new value. However, ag-data could also (and may already) be used 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. rent-seeking). In order to protect the interests of vulnerable stakeholders and the broader public, policymakers must beware and arrest the progression of agribusinesses leveraging ag-data toward these ends.

Approaching this policy problem is challenging, given the current paucity of well-defined and established legal and economic institutions controlling and leveraging ag-data flows. As such, this paper advances a behavioural approach to understanding the dynamics underlying a prospective market for ag-data. The first section identifies the policy problem and elaborates the challenges inherent to proactively governing *value-chain disruption* in agriculture and agri-foods. The second section provides background for key concepts and developments. The third section introduces the experimental methodology, results, and a brief analysis thereof. The paper concludes with a discussion of policy implications based on the experiment results, offering potential directions for further investigation.

Problem

This paper aims to confront governing digital disruption in the early stages. Against a backdrop of uncertainty and anticipation, it is impossible to depict a complete picture of what is to come, much less provide a set of definite policy prescriptions. That said, enough information is available to engage this emergent policy puzzle in pursuit of an outcome that best aligns with the public interest. Agribusiness leaders are beginning to reposition for the future and develop strategies to leverage ag-data.[6] Further, given the emergence of nascent markets for ag-data,[7] policymakers should think more about the transactional rules and conditions most conducive to innovation, efficiency, and mutual benefit among stakeholders. Such an environment would guarantee trust and predictability, and ensure that ag-data permeates existing industrial systems in ways that generate broad insights that drive positive-sum outcomes.

Though agribusinesses are forming structures to control and leverage ag-data in the private sphere, this area of activity lacks formal legal institutions: ag-data 'ownership' remains a misnomer outside of vague contracts that apply broadly (if at all) to generation, storage, sharing, transacting, and leveraging of ag-data.[8] There is a logic suggesting this ought to change. Classical economics, as explicitly formulated in the Coarse 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.[9] 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 it most—i.e. the

[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] Schrimpf, "Farmobile Addresses Data Transparency With New Legal Agreement."
[8] Janzen, "What Makes Ag Data 'Ownership' Unique."
[9] Coase, "The Problem of Social Cost."

party capable of using ag-data to generate the greatest economic value, thus producing the most *efficient* (if not necessarily most *equitable*) outcome.

However, 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 dimensions of this environment may elude the standard economic assumption that markets will efficiently coordinate exchanges given clearly-delineated property rights, regardless of their initial allocation.[10] Potential behavioural dynamics underlying ag-data exchange between producers and agribusinesses may impede Coasian bargaining, resulting in irrational outcomes that are neither *efficient* nor *equitable*. This could mean that it matters to whom property rights in ag-data are initially assigned, or that the practice of ag-data exchange is fraught with problems grounded in cognitive biases and irrational decision-making—made all the worse by the difficulties inherent to valuating ag-data, given persistent uncertainty surrounding its potential uses and their outcomes.

Approaching this question, it is sensible to start with producers, who remain the nexus of primary ag-production and likely have the least information with which to accurately valuate ag-data generated from their operations. Though producers are compelled by the demands of end-consumers and face pressure from either end of the value chain, they retain much agency over their commercial 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

[10] Coase.

tools; the sum of their individual choices dictates, in part, the availability and nutritional content of the food staples consumed by billions across the globe.[11]

As such, the choice architecture of *on-farm* decisions and the personal attributes of producers both matter tremendously. North American producers are characteristically independent and shrewdly skeptical of unproven technologies.[12] Yet technology is core to their production activities, which frequently absorb early waves of technological diffusion.[13] The adoption rate of *on-farm* innovations, as well as how producers use these tools, determine the volume, variety, and velocity of ag-data generated. This edifice of ag-data shapes future possibilities for *value-chain* ag-data use and its consequent pathways for creative destruction.[14]

Various literatures have investigated producer adoption of *on-farm* technologies.[15] Instead, this paper aims to simulate producer decision-making in a notional market for ag-data—data generated from *their* farm and through *their* production activities. A host of dimensions likely impact producers' valuation and decisions around ag-data, including their relationship with these data and the processes whereby these ag-data were generated. However, for policymakers, a sensible starting point may be to simulate how producers would behave were property rights clearly delineated. This paper applies a behavioral approach to one piece of a 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 the heart of all behavioural questions, 'Does starting point matter?'.[16] Behavioural science refers to when this question is answered in the affirmative as the

[11] Wolfert et al., "Big Data in Smart Farming – A Review."
[12] Sullivan, Interview with Bryan Sullivan, Farmer.
[13] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."
[14] Pfarrer and Smith, "Creative Destruction."
[15] Aubert, Schroeder, and Grimaudo, "IT as Enabler of Sustainable Farming."
[16] Kahneman, *Thinking, Fast and Slow*.

endowment effect—i.e. when the condition of ownership, itself, leads the owner to irrationally overvalue an asset qua possession.[17] Inversely, the *endowment effect* could be construed in terms of the condition of non-ownership causing the non-owner to undervalue an asset when faced with the choice to purchase said asset.

Further, the personality, temperament, and worldviews of a producer may also determine qualities such as his or her levels of risk-aversion, competitiveness, or even susceptibility to cognitive biases, thereby impacting decision-making. To further understand the dynamics underlying ag-data exchange, this paper also examines whether a producer's *worldview*—i.e. a cohesive viewpoint on political, economic, social issues—either counteracts or amplifies the presence of the endowment effect in his or her decision-making.

This paper draws from a conceptual framework on worldviews originated by Gilpin and further developed and adapted by Phillips.[18] This framework offers three distinct orientations. 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. The *liberal* worldview is characterized by prioritization of the individual, economic power, positive-sum dynamics, individualism, economics over politics, a laissez faire view of trade and globalization, and a market-driven process of innovation and economic development. Last, the *critical* worldview prioritizes identity-based groups, relational power between groups, negative-sum dynamics, group identity, a conflictual view of politics and economics, dependency-based view of trade and globalization, and the need for a socially-driven process of innovation and economic development.

[17] Hayes, "Endowment Effect."
[18] Gilpin, "Three Models of the Future."

Determining if and to what extent these dynamics influence ag-data transactions could greatly help policymakers understand the potential impacts of delineating ag-data ownership to producers versus agribusinesses, and whether Coasian bargaining is sufficient to realize outcomes that align with the public interest. To that end, this paper 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 do) influence outcomes in markets for ag-data market (existing or imminent). Answering these questions could help policymakers better understand whether they can trust Coasian bargaining to produce a favourable outcome, regardless of the starting allocations of ag-data ownership.

Background

The *On-Farm* Revolution*:* Precision Agriculture

Most discourse on the digitization of agriculture and agri-foods focusses on *on-farm* advancements in efficiency and productivity and evokes ambitions like the United Nations' Food and Agriculture Organization's (FAO) goal to increase food production by 60% to feed a projected 9 billion people by 2050.[19] However, the ongoing digital transformation of agribusiness has as much to do with capturing profits as the goals championed in international development slogans. Today, the five highest valued global companies are all data-driven technology firms.[20] There can be little doubt that agribusiness leaders are acutely focused on their own opportunities to capitalize on the vast quantities of data produced using their

[19] Food and Agriculture Organization of the United Nations, "Feeding Nine Billion in 2050."
[20] Morgan, "Amazon Becomes Third-Most Valuable Company in the World."

technologies. Indeed, in the wake of the broader ag-data revolution, closer examination reveals that there is more than feeding the world at stake.

However, none of this is to claim that recent *on-farm* advances amount to anything less than a revolution in ag-production.[21] Primary agriculture in the developed world has long been highly innovative,[22] evolving rapidly since the Green Revolution of the 1960s,[23] which was followed by vast improvements to machinery and the implementation of superior management practices.[24] Meanwhile, much of Asia, Africa and Latin American have remained largely "untouched by modern technology" in this regard.[25] Today's *on-farm* revolution is mostly defined under the broad category of 'precision agriculture.' Earliest developments date back to the 1980s[26] 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.). Consistently straight field rows had long been a hallmark of quality farming[27]; thus, 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 all but eliminated human error from seeding, spraying, and harvesting. '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 inputs in the same area more than once).[28] Today, most producers in the developed

[21] Bronson and Knezevic, "Food Studies Scholars Can No Longer Ignore the Rise of Big Data"; Carolan, "Publicising Food"; Cheng and Sonka, "Big Data."
[22] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[23] American Farm Bureau, "Farmers, Agriculture Technology Providers Reach Agreement on Big Data Privacy and Security Principles Expected to Accelerate Technology Adoption."
[24] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[25] Rehman et al.
[26] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."
[27] Aubert, Schroeder, and Grimaudo, "IT as Enabler of Sustainable Farming."
[28] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."

world have adopted GPS/GIS-guidance.[29] Moving into the future, the logical extension of this technology is fully-autonomous farm machinery, the first deployment of which was, in spring 2018, SeedMaster's autonomous Dot Power Platform.[30]

Building upon GPS/GIS-enabled 'autosteer' capabilities, a technology called *sectional control* represents the next degree of intensification in precision agriculture. Equipping to both sprayers and seeders, sectional control leverages GPS/GIS to automatically disable individual seeder rows or sprayer nozzles when the vehicle is outside a set boundary or passes over sections that have already been seeded, fertilized, or sprayed.[31] 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 thousands in costs for seed, fertilizer, pesticides, herbicides, and other inputs.[32]

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*- and (particularly) *off-farm value-chain* transformation driven by ag-data.[33] This shift was enabled by recent reductions in the cost of sensors as a production input, as well as ID-related advancements in computing.[34] However, the sudden ubiquity of sensors in ag-machinery is likely also a testament to the speculative, *off-farm* value of ag-data, which communicates valuable information (i.e. soil,

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

climate, seed, input and application decisions, and yield) that helps predict the future global food supply across varies geographies.[35]

Moreover, this flood of sensors into new ag-equipment has also come in the form of unmanned aerial vehicles (UAVs),[36] which collect infrared, multispectral, or thermal infrared data that are digitally rendered to produce actionable assessments of crop health, elevation, and input distribution.[37] Farm management software analyses, 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.[38] 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 emergence of agriculture within the data economy *writ large*.

Though "farming has been empirically driven for over a century,"[39] a new degree of digital 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 ag-production processes.[40] Far from replacing human decision-making, these technologies can empower producers to make better-informed decisions, in real time, based on statistically-significant data.

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

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[35] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."
[36] Burwood-Taylor, Tilney, and Chauhan, "AgTech Investing Report: Mid-Year 2016."
[37] Green Aero Tech, *Aerial Imaging Services for Agriculture*.
[38] Green Aero Tech, *The Complete Solution for Aerial Mapping*.
[39] Bronson and Knezevic, "Big Data in Food and Agriculture." 1.
[40] Koumakhov, "Conventions in Herbert Simon's Theory of Bounded Rationality."

unique field locations. Based on geographical location, VRT-enabled equipment varies input application rates by shutting on and off individual components as necessary.[41] Prescriptions are ultimately determined by the agronomic information corresponding to precise locations, including soil health, elevation, and NDVI maps of vegetative health.[42] VRT also enables seeders and sprayers to navigate more challenging topographies by varying application rates to match elevation-based growth capacity.[43]

Today, VRT adoption remains slow due mainly to the high costs and steep learning curve associated with the technology. For many, the cumulative fixed cost for the full suite of precision technologies is prohibitive considering its return on investment can still vary greatly due to weather. Many producers also face liquidity constraints and tight profit margins,[44] and competition has driven the need to maintain margins via economies of scale. This drive to consolidation has seen many small- and medium-sized producers either exit the market or hold on tenuously at the limits of their tolerance for risk.[45] Nevertheless, experts still project 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.

Last, the smartphone has become increasingly central to precision agriculture systems.[46] Sensors have enabled agribusinesses to offer many new products, such as hardware devices that monitor commodity volumes, heat and moisture content of stored commodities, irrigation cycles, and many other key production metrics. Smartphones serve as a universal remote-control device

[41] Suprem, Mahalik, and Kim, "A Review on Application of Technology Systems, Standards and Interfaces for Agriculture and Food Sector."
[42] Mondal and Tweari, "Present Status of Precision Farming."
[43] Norac, TopCon Positioning Group, *Boom Height Control*.
[44] Rehman et al., "Modern Agricultural Technology Adoption Its Importance, Role and Usage for the Improvement of Agriculture."
[45] Lowy, "Monsanto Is Bridging Genetics and Big Data Analytics."
[46] Tene and Polonetsky, "Privacy in the Age of Big Data."

to monitor and operate a range of systems.[47] 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.[48]

All aforementioned technologies embody the 'precision agriculture' concept, though this brief ocerview barely scratched the surface of a bounty of innovations overcoming ag-production problems. These innovations provide context for *why* and *how* ag-data are being generated, creating the potential for a broader *value-chain* revolution, which could deliver equal or greater impact once ag-data from farms migrates to food processing facilities, financial intelligence services, R&D projects, blockchains, and anywhere else new value could potentially emerge.

The *Value-chain* Revolution: 'Big Data' and Beyond

There is evidence that various agribusiness players are collecting ag-data for purposes that fall outside of "*on farm*" use for ag-production. Each day, hundreds of thousands of farms across the developed world collect vast quantities of data expressing yield, moisture, climate, soil and input application, and much more. This is highly-valuable information because ag-data can describe or directly impact many vital processes and outcomes in primary production—for example, whether certain foods or ingredients will be consistently available to consumers, the quality of nutrition available to hundreds of millions, and the price of food. If these outcomes are important for people qua *citizens* and *consumers*, ag-data is important to agribusinesses in innumerable ways.

Most technology experts feel strongly that no industry is immune to disruption from data-driven technologies. Today's executives from every industry are looking to Silicon Valley and

[47] Aubert, Schroeder, and Grimaudo, "IT as Enabler of Sustainable Farming."
[48] Mulla, "Twenty Five Years of Remote Sensing in Precision Agriculture."

the promise of 'big data'—i.e. the value of novel insights drawn from analysing troves of aggregated data;[49] concurrently, the last few years have seen data technology start to transform a variety of sectors, including business, finance, and healthcare.[50] Mayer-Schonberger and Cukier hailed this paradigm shift in their seminal *Big Data*, published in 2014, foretelling a new technology called 'big data' "migrating to all areas of the human endeavor." The authors pointed out that, even just five years prior to 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"[51]—did not exist and could not have. In part, this is because the amount of computing power and storage necessary to draw insights from massive datasets had previously been too expensive. However, more importantly, 'big data' required a paradigm shift 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."[52]

However, in the agri-foods context, the notion of 'big data' must be handled carefully; though it is certainly one the most important forms of data-driven disruption, data can also be extremely powerful, in its granularity, at lower volumes. On the other hand, scale is *the* defining feature of 'big data': the label applies only when a certain volume threshold is satisfied, whereupon a "change in scale" leads to a "change in state" and a quantitative change becomes a qualitative one.[53] This distinction may be quite germane in the agri-food context—particularly in that it likely maps roughly onto the distinction between *on-farm* and *value-chain* use cases for ag-data. In the context of the *on-farm revolution*, sensors and UAVs *on a farm* collect data about

[49] Chen, Chiang, and Storey, "Business Intelligence and Analytics: From Big Data to Big Impact."
[50] Henke et al., "The Age of Analytics: Competing in a Data-Driven World."
[51] Mayer-Schönberger and Cukier, *Big Data*.
[52] Mayer-Schönberger and Cukier.
[53] Mayer-Schönberger and Cukier.

the conditions *of that farm* to harness precision agriculture capabilities to intensify productive capacity *of that farm*. By contrast, the *value-chain* ag-data transformation entails the mass aggregation of data at the regional, national or international level for means that produce more complex ends.

As precision farming technology inches toward widespread adoption, agribusinesses stand to profit considerably from establishing a new catalogue of products and services that further automate and add precision to ag-production processes. Agribusiness, by definition, revolves around selling products and services to producers that maximize the productivity and efficiency of farming operations. The act of producers transmitting *individualized* ag-data to agribusinesses to power precision agriculture technologies precipitates a positive-sum impact wherein both farmers and agribusinesses are better off. However, leveraging individualized ag-data does not meet the 'big data' volume threshold;[54] no single farm is 'big' enough. To truly conceive of big data in this space is to consider the possibilities that arise from aggregating and analysing ag-data from several—and up thousands or even millions—of farms to uncover new insights and value.

What could be achieved by analyzing data collected from an enormous volume of farming operations extending over diverse soil types and climates across space and time? Perhaps commodity traders could predict regional growth outcomes for crops valued at millions of dollars far before harvest? Alternatively, perhaps early signs of regional crop failure or disease could be identified in time to preserve millions of bushels in harvested crop otherwise lost if not for insights derived from aggregated ag-data. And what about the impact further downstream in

[54] Manning, "What Is Ag Big Data? How 8 Companies Are Approaching It."

the agri-food supply chain in marketing to end-consumers?[55] The answers to these questions will emerge as the *value-chain* ag-data revolution takes full force.

This paper sets out three broad categories for ag-data use. First, *primary use* refers to leveraging ag-data to improve ag-production: *on-farm* use (e.g. precision agriculture) that produces positive-sum benefits reaped by producers and agribusinesses alike. *Secondary use* refers to *off-farm* use cases for ag-data that produce zero-sum outcomes resulting in value migrating from producers to agri-businesses (e.g. commodity speculation). Last, *tertiary use* refers to *off-farm* use cases that produce positive-sum outcomes with benefit accruing to agribusinesses but leaving producers no worse off (e.g. targeted marketing, product and end-user design, supply chain and logistics management, risk mitigation, and improved traceability and sustainability). These definitions will be relevant in the Policy Implications section of this paper.

Method

This study employed a behavioural methodology to test for the presence of an endowment effect in the valuation of ag-data. The population of interest was agricultural producers, with undergraduate agriculture students surveyed as a proxy. In total, 137 participants were asked to valuate property rights in ag-data in a simulated scenario that presented them with uncertain opportunities (attached to ownership) and uncertain risks (attached to non-ownership). The experiment adopted a between-group design, randomly assigning one of the two treatments; 65 participants received Treatment 1 and 72 Treatment 2. The first treatment assigned property rights in ag-data to the participant (i.e. producer) and asked the *minimum price* at which he or she would be willing to sell ownership. Conversely, the second treatment assigned property rights in

[55] Prno and Scott Slocombe, “Exploring the Origins of ‘Social License to Operate’ in the Mining Sector.”

ag-data to a fictional agribusiness firm and asked the *maximum price* each participant would pay to acquire ownership. In both treatments, respondents were presented with a range of dollar values for data rights per acre, beginning at '$0' and ending at 'more than $18.'

An endowment effect is recognized if the mean price within the first group exceeds the mean price within the second group and this difference is statistically significant. What makes the endowment effect irrational is that the condition of ownership should have no bearing on how much an object is to worth to an individual. In the case of ag-data, the most relevant value determinants should be (1) what value the individual can leverage from the using the ag-data and (2) what potential risks the individual can mitigate through retaining exclusive rights over ag-data. However, given the uncertainty about *how these data could be used*, producers cannot accurately gauge the true present value of ownership and must, instead, transact largely based on irrational, biased decision making.[56]

Following this experiment testing for the endowment effect, the survey presented six questions probing respondents' views on technology in terms of its pace of advancement and impact on the economy, society, and individuals. Following this section were nine questions, most of which offered three answers corresponding, respectively, to one of the three worldviews—i.e. *Realist*, *Liberal*, and *Critical* (respondents could also choose "I don't know" as an answer). With one point per answer, each participant accumulated a tally representing the degree of their orientation toward each worldview. One question also offered limited set of 'worldview-neutral' answers respondents could choose. As eluded earlier, the purpose of this section was to probe whether adherence to a particular 'worldview' could either amplify or

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

lessen the endowment effect in a subject's decision-making. A Spearman's Rank Correlation test was used to measure correlations between worldview and other variables.

Results

Analysis discovered a mean valuation of $11.6 for Group 1 while the mean valuation for Group 2 was only $7, a difference of 65.7%. An Unpaired Two-Samples Wilcoxon Test verified the statistical significance of this difference, producing a p-value of 1.549e-06. This result contradicts rational-actor assumptions, given that that the condition of ownership should have no impact on a rational actor's valuation of ag-data. In a population of n=137 comprised entirely of perfectly-rational actors, the difference in mean between Group 1 and 2 would be quite negligible the higher mean, should one exist, would favour neither group in particular. Without question, a statistically-significant difference in mean on the order of 65.7% constitutes clear evidence for the presence of the endowment effect. This suggests that the pre-assignment property rights in ag-data, whether to a producers or agribusiness, could impede Coasian bargaining to produce an *inefficient*—and also potentially *inequitable*—economic outcome. Further, results suggest the endowment effect was more pronounced in respondents adhering to a 'realist' worldview and less pronounced in those adhering to a 'critical' worldview.

Policy Implications

The results of the experiment revealed that the endowment may play a significant role in producers' valuation of property rights in ag-data. This section examines the potential implications of the endowment effect as an impediment to Coasian bargaining. At a time when much about the digital transformation of agriculture and agri-foods remains highly uncertain, this result reveals a robust dynamic inherent to producers' decision-making vis-à-vis ag-data transaction. The endowment effect is not a feature of the economic environment, but rather consists in the structure of the human mind, which behavioural economics shows is often shockingly susceptible to systematic errors.[57] 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 (i.e. for producers, ag-data is worth the protection from *secondary* exploitation it provides). On the other hand, agribusinesses, as the practitioners of *secondary* and *tertiary* ag-data use, are likely much better equipped to valuate ag-data in terms of its benefits to them. Currently, agribusinesses collect ag-data for free and, by this point, have likely developed some sense of its worth.

This section attempts to construct a simple model, incorporating a handful of assumptions and flexible parameters, to test whether the endowment effect could impede Coasian bargaining. The model features two actors—the producer and the agribusiness. Each is meant represent the aggregate of producers and agribusinesses, respectively. 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

[57] Kahneman.

the secondary use category. *Secondary use* occurs only if agribusiness 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 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.

Accounting for *primary*, *secondary*, and *tertiary* use, property rights in ag-data are worth 20 to agribusiness and only 10 to the producer. Given this difference, Coasian logic holds that every bargaining scenario between rational actors would necessary result in agribusiness owning ag-data (again, either by pre-assignment or through exchange).

Figure 1 depicts the potential outcomes of Coasian bargaining under the assumption that the agribusiness values ag-data more than the producer and 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 1: Higher Agribusiness Valuation & No Endowment Effect

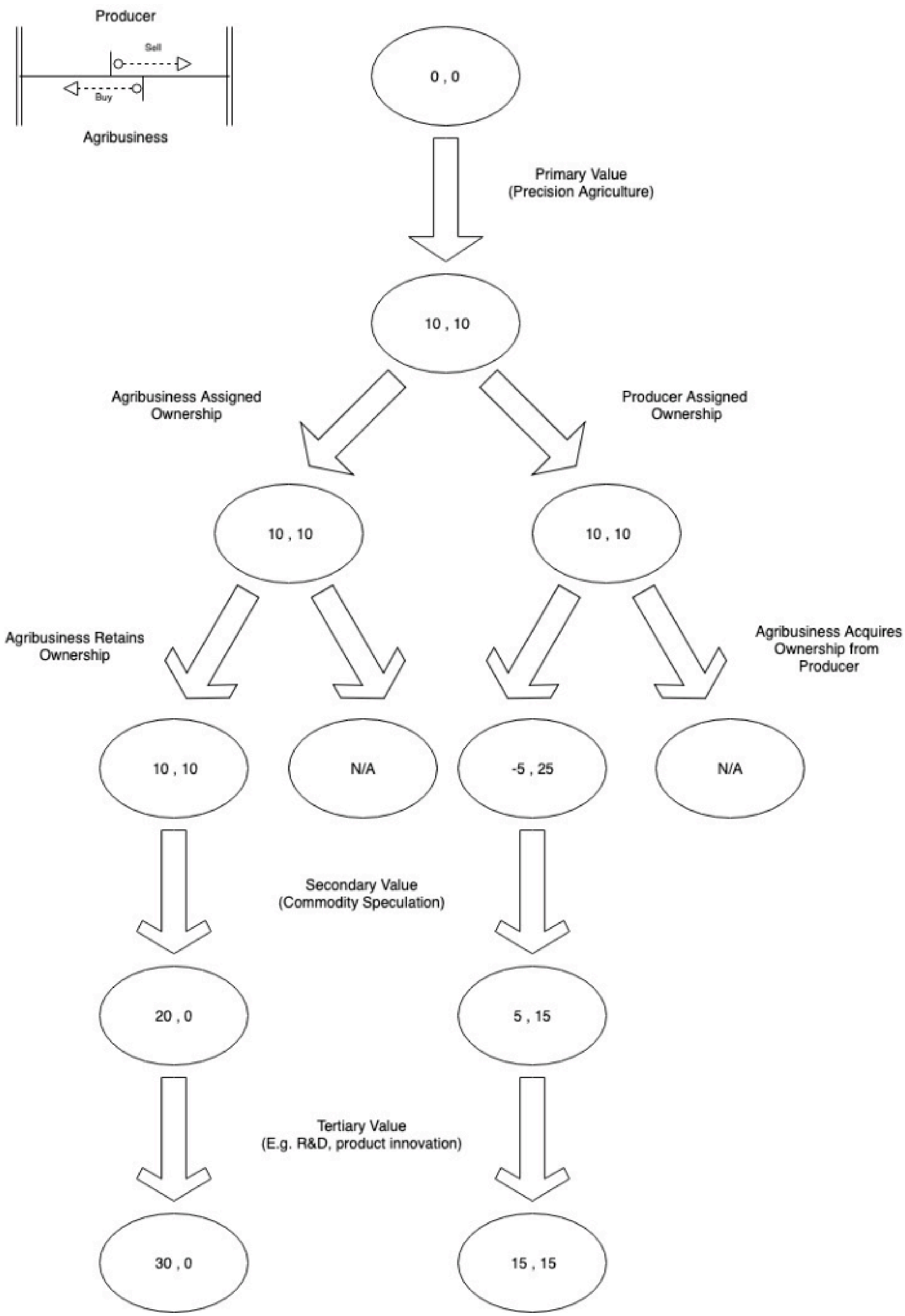
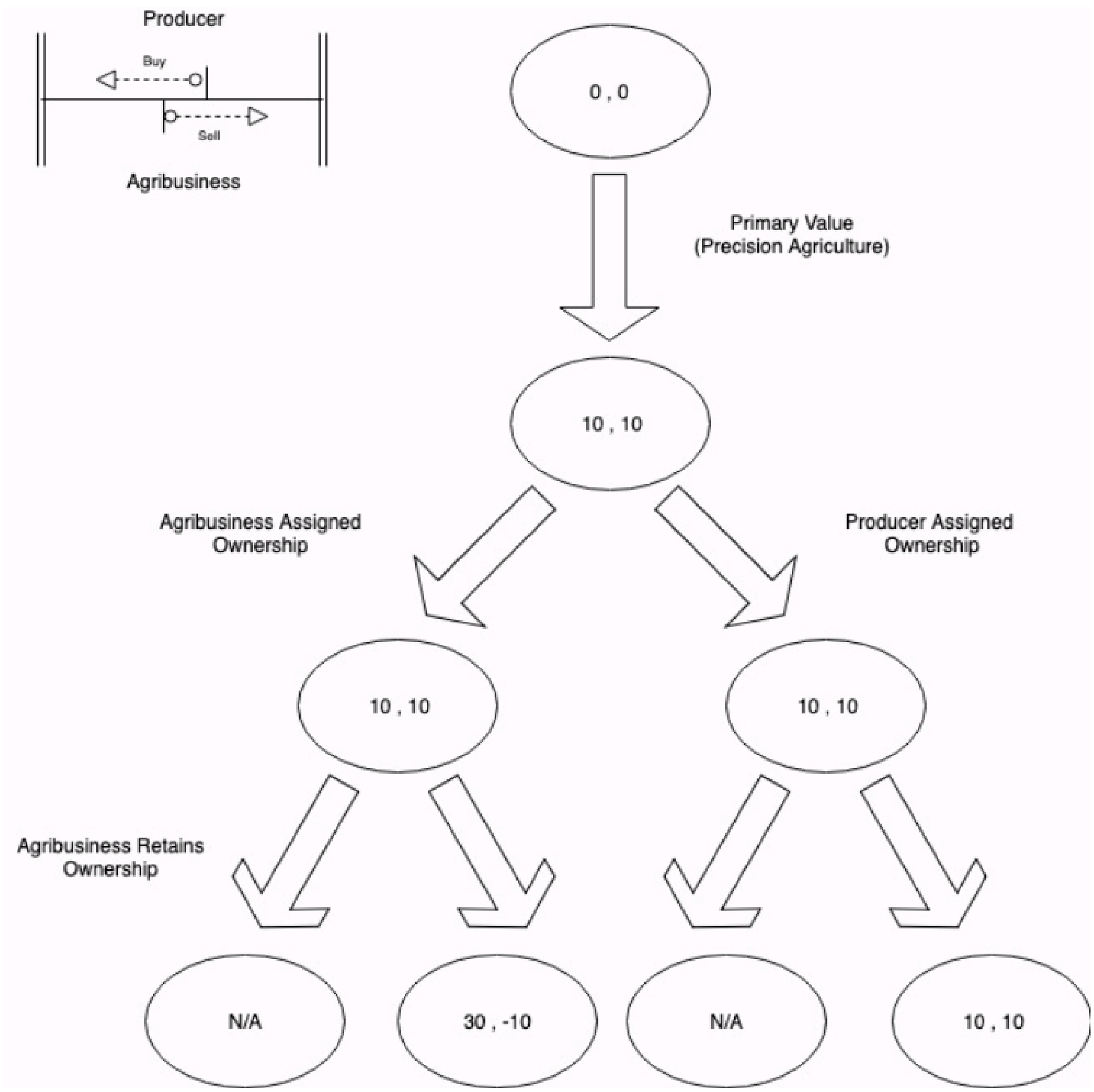


Figure 2 depicts the potential outcomes of Coasian bargaining under the assumption that the producer (irrationally) values ag-data more than the agribusiness and no endowment effect is present. In this case, assigning property rights to the agribusiness results in the worst possible outcomes for the 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

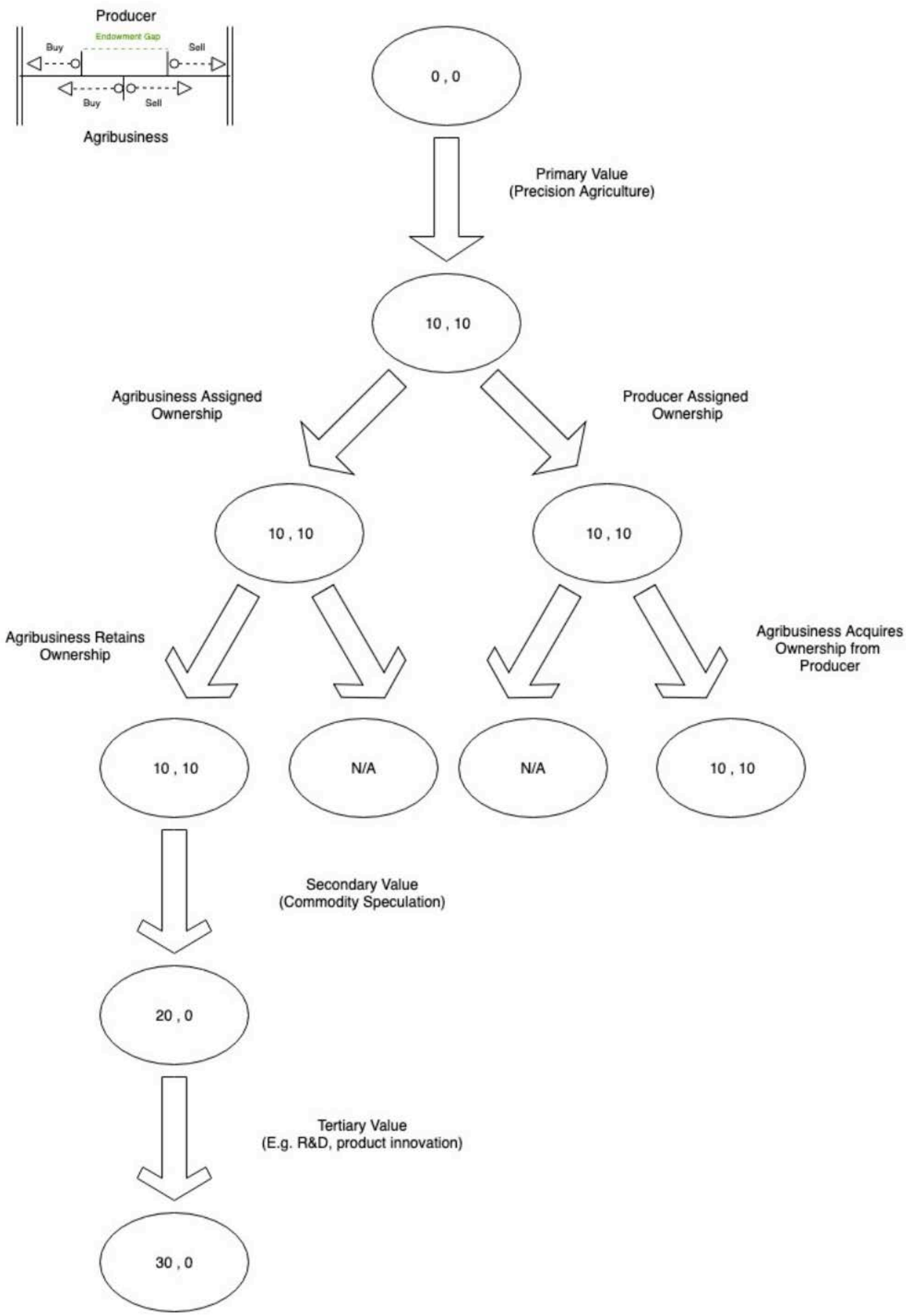
Figure 2: Higher Producer Valuation & No Endowment Effect



economy; the outcome is poor in terms of *equity* because the producer is left at 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 poor in terms of *efficiency*. 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*.

Of the two configurations above, the second—wherein in the producers' starting valuation is pegged to a spot that overvalues ag-data—would not likely occur absent the influence of behavioural factors such as the endowment effect. However, the results of the experiment strongly indicate the presence of the endowment effect in producers' valuations, suggesting that producer overvaluation could actually impede Coasian bargaining toward an *efficient* outcome. Figure 3 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 the 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 for which is more than offset trough the value generated by a combination of *secondary* and *tertiary* use). The wider the 'endowment gap,' the higher the chances an agribusinesses unified 'strike price' (the same whether *buying* or *selling*) will all within this gap, which nullifies effective Coasian bargaining.

Figure 3: The Endowment Effect



Conclusion

In conclusion, the endowment effect reveals that policymakers likely should not place too much faith in the ability of free markets for ag-data to produce Pareto-efficient outcomes. Given that *secondary use* benefits agribusinesses at the expense of the producer and *tertiary use* only yields marginal benefit for the agribusinesses, assigning ownership to the producer is always advantageous in terms of equity. However, if the endowment effect increases producer valuations to a point greater than the rational valuation of the agribusiness, assigning initial ownership to the producer may actually result in an *inefficient* outcome that deprives the economy of *tertiary* value.

A broader lesson is that even clearly-defined property rights (and sufficiently low transaction costs) may not lead to *efficient* market outcomes and, because participants are so often irrational, markets can be imperfect mechanisms for distribution. This may become increasingly true as new data-driven technologies enable new forms of disruption and value migration. Classical economic theory holds that the most efficient allocation of resources is at hand when resources are possessed by those who value them most, which, if the minimal necessary conditions are in place, will be sorted out by the market.[58] However, actors can only coordinate on behalf of producing the optimal economic outcome if they can properly valuate data based on adequate information about the opportunities and risks associated with use that data. As such, beyond establishing a clear system of property rights in ag-data, it may be necessary for policy to demand a much higher degree of transparency from agribusinesses using ag-data to ensure producers can accurately account for risks of *secondary use*. Conversely, this would also help producers better understand the limits of such risks to discourage them from

[58] Coase, "The Problem of Social Cost."

overvaluing ag-data rights. However, even with more transparency, the complications introduced by the endowment effect (and likely other behavioural factors) could nullify the effectiveness of ag-data markets to a degree that is fundamentally unacceptable. In any case, more research into the dynamics underlying ag-data exchange is needed so that policymakers can move toward a subtler and more effective approach to governing broad ag-data disruption across the agriculture and agri-foods supply chain.

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