Information Age Agriculture: Commodity Concept and Automation

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Abstract

What constitutes a commodity is circumscribed by the pertaining technology and by incentives. Biotechnology innovations allow for more consistent production while sensors and other information technologies have allowed for improved discernment of material attributes. These two innovation classes are underpinning deep structural change in how agricultural products are produced, transformed and marketed. Since the beginnings of the Industrial Revolution, standardization of materials and equipment have enabled machinery to replace labor that can deal with non-standard decisions. Witless machines are now being replaced by discerning machines, allowing capital to compete with labor in new ways. When there are two underlying raw materials types, this paper provides a Bayesian information processing model of production and processing where three parameters matter. The state of biotechnology determines product consistency, and so the prior information that a resource receives when handling raw materials. Handling resources vary in the quality of the signal that is read from the materials. Finally, incentives determine tolerance for mis-categorization of raw materials types. We show that produce consistency and discernment substitute when the costs of mis-categorizing are symmetric. Then low discernment costs promote differentiation while low costs for consistent materials promote commodity production. When mis-categorization costs are asymmetric and penalize more heavily mis-categorization into the more prevalent type then discernment and consistency can complement at low consistency levels but will substitute at higher consistency levels. Furthermore, commodity production will occur whenever consistency is close to 100% or to 50%. A Slingshot Effect can occur for materials consistency whereby improved biotechnology first increases demand for both discernment and consistency, through complementarity, but then eliminates demand for discernment and further boosts demand for consistency because the pair have become substitutes. Finally when sorting frictions, i.e., switching costs, decrease due to the advent of automation technologies then product differentiation is promoted. The model adapts to pure production cost settings where raw material types are replaced by input needs.

Key words: agricultural labor, automation, Bayes' rule, precision agriculture, product differentiation, smart capital

JEL codes: D24, J23, Q13

The word 'commodity' is commonly understood to mean a useful item available at a given time and location that is mass-produced and unspecialized. It is pertinent then to ask why so many products are unspecialized. The stock answer appeals to economies of scale and transactions costs. Lower transactions costs, learning economies, network effects and a variety of other features can lead to reduced unit costs when treating goods as if they were the same while value differences are insufficient to support plural markets. Although soundly reasoned, it assumes that distinctions are readily detected and this is not always the case. The distinction needs to be made between units of a commodity being the same and being treated the same due to want of information. Hard to detect differences exist in agricultural commodities because of genotype and phenotype distinctions, of environmental factors arising during production and transformation, and of interactions between the two. Such differences exist in natural resource commodities because of geological heterogeneities, among other reasons. They even exist in manufactured commodities, such as microchips, because of heterogeneities in raw materials, proprietary technologies and slight environmental variations arising during manufacture.

The main thesis of this work is that the ability to detect differences cheaply is a core determinant of both commodity form and how automation in agriculture has evolved. Sensing technologies, both mechanical and biological in kind, are expected by many to continue their rapid expansion in agricultural and food production (National Academies 2019). Agriculture was in some ways an early adopter of mechanization (Page 1996; Lakwete 2003), but the waves of innovation that swept the general economies of the world's more industrialized areas did not affect food and, more so, agricultural production in the typical way.

Regarding the comparative demand for labor skill levels, Braverman (1974) and Caselli (1999) are among the many who have documented and sought explanations for two distinct, and sequential, trends in responses to technological innovation over time. First came a trend toward technology-induced skill-reduction early in the 20th Century as Fordist process-oriented approaches transformed manufacturing. Then came an information technology (IT) driven trend toward skill enhancement in more recent times (Bresnahan et al. 2002; Frey and Osborne 2017).[1]

Economic analysis of agricultural mechanization has focused primarily on capital-labor substitution (Schmitz and Seckler 1970; Huffman 2012; Gallardo and Zilberman 2016; Charlton et al. 2019). Replacing labor with capital can provide major cost savings while in many cases the primary motivation has been either to comply with labor and other laws or to permanently secure resource needs. Our concerns are not with the desire to substitute capital for labor but rather with what enables it to happen. Although education levels among agricultural workers is generally not high, this is seldom mentioned as a motive for replacement. Rather, the concern has been the reverse. Capital has not been sufficiently capable of subtle discernment and dexterity that most physically robust agricultural workers bring to their tasks. Machines can deal with the menial tasks but less so with information processing, judgement and nuance.

In the agricultural and food sectors, deskilling due to mechanization has tended to lag the general economy in part because barns and fields provide rougher conditions than factory floors and roads. Draft horses, and so the need for operators, persisted in U.S. agriculture long after trucks had replaced true horsepower in other settings: farm tractors surpassed draught animals during World War II (Olmstead and Rhode 2001). The post-war years saw developments in market inputs, such as pesticides, that likely reduced the need for crop husbandry skills (Vandeman 1995). Where relevant, the advent of the over-the-top glyphosate technology has likely reduced the need for scouting information and skills and even for cultivation (Perry et al. 2016). In comparison with other sectors of modern economies, agriculture and food production has not been a major IT user (Gandhi et al. 2016; Antle 2019), in large part once more because barns and fields are not factory floors and roads.

Agriculture and food have presented major challenges to automation. Zhang (2018) has written

> "To make machines operate efficiently, one feature of mechanized production is the uniformity

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[1] As Page (1996) notes, Henry Ford was impressed by how mechanical aids were used along a line in mid-western meatpacking industry. The distinguishing feature in Ford's approach was the high levels of standardization (Hounshell 1984) possible in a manufacturing process but not at that time when working with agricultural produce (Goodman et al. 1987).

> of operation in a field. Even though tree fruit production is quite different from field crop production, many of the fundamental mechanization technologies for field crop production can be used directly or modified for use in tree fruit production. The uniformity of mechanized production increases efficiency at the expense of being able to respond to crop growth variabilities often caused by inter- or intra-field soil type, fertility and moisture variance."

Shamshiri et al (2018) elaborate as follows

> "While many are in still in the prototype phase, these robots are now capable of performing various farm operations, including crop scouting, pest and weed control, harvesting, targeted spraying, pruning, milking, Phenotyping, and sorting. Unlike the industrial case, these applications can be extremely challenging to be fully automated. An agricultural robot is subjected to an extremely dynamic environment, and yet expected to touch, sense, or manipulate the crop and surroundings in a precise manner which makes it necessary to have the minimal amount of impact while increasing efficiency."

Much attention has been devoted in the agricultural economics literature to the deepening use of precision agriculture, big data and related methods. The work has pointed to far-reaching implications for environmental policy (Finger et al. 2019), crop productivity assessment (Lobell et al. 2020), and risk management (Yu and Hendricks 2020). Bayesian decision theoretic models have been used in that literature (Babcock et al. 1996) and at the interface between production and consumption (Thompson et al. 2017). But these are largely seen as support tools and when seen as part of the production process are taken to provide new value to some factor, typically capital. Information is viewed as allowing machinery to do more but not as replacing what labor or entrepreneurship do. The perspective that these information sources are substituting for agricultural and food sector labor has not, to the best of our knowledge, been formally modeled.

A literature has emerged on how automation-focused IT is affecting factor demand in the economy at large. As reviewed in Acemoglu and Restrepo (2018a, 2018b, 2019), the more traditional approach has been to view automation as capital-augmenting, and so increasing the marginal value of capital in comparison to that of labor so that competitive forces lead to replacement of labor with augmented capital. This is a shotgun approach as it is constrained in distinguishing between labor forms and so has little to relate about why skilled labor has tended to fare better than unskilled labor as automation gains traction in an economy. Acemoglu and Restrepo (2018a, 2018b, 2019) have taken a more granular, and realistic, perspective on factor use by characterizing a menu of task each of which can be completed by capital or labor but where the factors differ in comparative advantage.

We find this approach to be appealing for the agricultural context because there is considerable regularity in what tasks have and have not been mechanized over time and also, as somewhat of an aside, in what commodities continue to be produced on more traditionally structured family farms (Allen and Lueck 1998, 2004). However the Acemoglu and Restrepo task-based model does not articulate the distinctions between tasks and where the comparative advantage comes from. We argue, and will include into a model, that capital's comparative advantage on tasks has been in exploiting what may be labeled as uniformity, standard settings and consistency. Thus mechanization came earlier to the factory than the field. Labor's comparative advantage on tasks has been in accommodating inconsistencies so that a labor focus persisted in agricultural environments that did not yield to standardization. But with the advent of IT, and especially sensing technologies, that comparative advantage is eroding.

In this paper we do two things. We offer a Bayes risk function model of decision-making under imperfect, but symmetric, information. Stated differently, we study a production technology where the output is a decision. This model is used to explain product differentiation and preferences over factors but can also be used to characterize farm management choices in the presence of sensor information. In addition to studying static decision-making we seek further realism by placing a frictional cost on changing a decision. These costs are important in agriculture and food production because product is typically bulky and decisions are invariably attached to energy-using actions. The costs are also important because automation-related technical improvements have likely decreased these costs over time.

Secondly, we relate the above analysis to two technological revolutions, biotechnology and information technology (Gallardo and Sauer 2018; Zilberman 2019), that are fundamentally altering agricultural production, food processing, retail and consumption. These revolutions are, in our view, very much proceeding in concert and their connections are at the root of 'commodity' as an economic concept. Our perspective on the two revolutions is statistical and emphasizes automation. Much of agriculture has resisted mechanization in times past in large part because of a technology impasse, namely an inability to deal with irregularities that originate in nature (Allen and Lueck 1998, 2004). Machines were of limited use to the extent that they could not deal with inconsistent product and this constrained competence in efficiently using resources through high throughput (Chandler 1992; Boehlje 1996), to differentiate produce (Hennessy et al. 2004) and deepen processing (Hennessy 2007).

There are two possible approaches to addressing this technology impasse and our Bayes risk model has equally prominent roles for both. One is to promote consistency so that the impasse is circumvented. Here biotechnology has played a prominent role through genetics to provide more uniform biological materials (Knorr and Sinskey 1985; Belter et al. 1994). Other technologies such as confinement, irrigation, uniform nutrients and nutrient applications have also played roles. For instance, giberellins and other plant growth regulators have for many years been used to ensure uniform growth rates, coloration and maturation (Wittwer and Bukovac 1958) and used on a wide array of commercially important crops. In a statistical sense consistency provides the prior information for our Bayes risk model. The other approach is to learn about and accommodate the distinctions. Here information technology, and in particular sensing to sort and pre-sort, is increasingly being used in agricultural production and food processing (Hennessy 2005; Vázquez-Arellano et al. 2016; Miao and Hennessy 2015; Zhang 2018; Tripodi 2018). These are the Bayes risk model signals.

Two harvesting problems, one recent and one much older, serve to illustrate the interplay between prior and signal in agricultural mechanization. Gallardo and Zilberman (2016) have studied the extension of mechanical harvesters in the highbush blueberry industry from berries destined for the processed market to berries destined for the fresh market. The machines would substantially reduce labor costs and reduce food safety risks. However, humans are adaptable to picking and current machines produce high fractions of damaged fruit, leading to low revenues in fresh markets. Fruit loss through clumsy mechanical harvesting is a second disadvantage. Consequently, profit calculations have not supported investment in mechanical harvesters.

Schmitz and Seckler (1970) have shown what may be required to make the transition. California tomatoes for processing shifted from hand-picked to mechanically harvested over the period 1964-1970. But the ground was laid two decades earlier when University of California, Davis, scientists bred a tomato variety line, VF 145 and derived strains, that was sufficiently hardy for mechanical handling and ripened uniformly (Rasmussen 1968; Webb and Bruce 1968). This, together with field levelling, continuous irrigation, carefully managed fertilization and seedling transplantation to ensure uniform growth, provided the consistent statistical prior.[2]

The tomato harvester was expensive to operate, in large part because a dozen workers were required to separate quality, ripe tomatoes from green or blemished fruit and from dirt. The signal, while perhaps strong, was costly. Noteworthy here are the two forms of loss. One can grade leniently by accepting with a certain probability material that will harm product reputation or prove difficult to process. Alternatively, one can grade harshly and lose good fruit. Discernment is critical where noisy signals or costly measurement and subsequent action will render the investment unprofitable. By the middle 1970s the loss calculations had changed as most of the workers had been replaced by accurate color-reading electronic sensors linked to an air-blaster for removed unacceptable tomatoes (Huffman 2012). Electronic sensors replaced human sensors, reducing switching frictions and so making the sensor signals more valuable even if of the same information quality.

The paper first presents the basic Bayes risk modeling framework with materials consistency as prior and resource-embedded sensor as signal. The setting is that of two material types with distinct market outlets and the focus is on whether marketing into separate markets is more profitable. In this model losses are held to be symmetric and output market prices are the same. Investment incentives for improving the prior and signal are then calculated and assessed. Loss asymmetry and market price

[2] Uniformity to ensure a consistent harvest is a pervasive technology theme in agriculture. Desiccation to promote consistent ripening is not applied to tomatoes but is applied to many other crops.

asymmetry are then introduced, followed by a consideration of how frictions affect investment incentives. The paper concludes with a brief discussion on alternative applications and on further lines of inquiry.

Basic Model

There are two raw materials types, *A* and *B*, available for discernment, possible differentiation and subsequent transformation. These materials characterize the universe of matter under consideration. The point of discernment can be at harvest, at a commodity intake point or during processing. Capacity allocated to discernment can take labor form, as in a worker charged with sorting. Alternatively it can take capital form, as in a sensor-enabled machine. We will use the terms 'capacity', 'resource' and 'factor' interchangeably when referring to the asset in which discernment is embedded. One unit of such capacity must make a single decision concerning the raw materials. For convenience in communication, whether labor or capital we will personify the resource by asserting that it can make decisions where of course an algorithm 'makes' decisions for capital.

Fraction $x \in [0.5,1] \subset \mathbb{R}$ of raw materials is type *A* while the residual fraction is type *B*. We refer to x as the consistency index because raw materials become more consistent in type as the value of x increases from 0.5 to 1.[3] One view of what x measures is biotechnology or genetic innovation because an enhanced ability to control genetics will allow for increased product consistency. We assume throughout that capacity is managed in a way that is compatible with the minimization of food item expected loss. Consistency parameterizes one aspect of how we view a commodity, at least in an economic sense, namely the 'no difference' part of item *i*) below.

Definition 1. A set of raw materials is a commodity whenever *i*) no difference can be discerned between subsets to be sold, or *ii*) differences can be discerned but markets provide insufficient

[3] In adaptations of this model to address more involved information environments, fraction x could also be viewed more generically as the stock of prior information available about the raw materials at hand.

incentives to do so.

Two further parameters are required to formalize the definition, one characterizing information processing and the other providing incentives. When handling raw materials, capacity will receive one of two signals about the materials, $s \in \{a, b\}$, with lower case signaling the corresponding upper case true type. Capacity differs along one dimension, namely by the capacity unit's discernment index, z, the cardinal meaning of which is as follows. If a capacity unit has discernment level z then fraction z of material type *A* signals as type *A*, i.e., $s = a$. One may think of the parameter as reflecting the test sensitivity that is embedded in the resource (Fawcett 2006).[4] One view of what z measures is information technology innovation because more informed data and better data processing will allow for enhanced discernment. Whether this signal is obtained from formal assessment, experience and intuition, machine learning or any other means is of no relevance for our purposes. Thus the probability of signaling as type *A* given that type really is *A* is $P(a \mid A, z) = z$ where $P(\cdot)$ represents probability and $P(\cdot \mid I)$ represents the appropriate probability conditional on information I. Restricting $z \in [0.5, 1] \subset \mathbb{R}$, we also impose that signaling as Type *B* given that type really is *B* as $P(b \mid B, z) = z$.[5,6] Thus a larger z value reflects greater competence as a decision-maker and $z = 0.5$ represents complete absence of discernment. Table 1 describes the information structure. We summarize our two main domain restrictions as,

Premise 1. Taking real number values, raw materials shares satisfy $x \in [0.5, 1]$ of Type *A* and the

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[4] Alternative perspectives on what z measures could include absence of noise in the environment, functional intelligence in interpreting noiseless signals or physical dexterity after clearly interpreting a noiseless signal. That is, the model to follow could be largely adapted to address a variety of failures when seeking to appropriately manage heterogeneous materials.

[5] We impose symmetry in signal structure in order to simplify notation. For our purposes, the constraint comes at no compromise to insights that may be obtained. This symmetry ensures that test specificity (the proportion of actual non-*A* types that are identified as non-*A* types), is also equal to z.

[6] Although errors can be viewed as either false rejection of Type *A* or false acceptance of Type *A*, we will not write of types I and II errors here because this might confuse given that neither *A* nor *B* are in the conventional sense hypotheses to be investigated.

residual $1-x$ of Type *B*. The share index may be taken as a measure of materials consistency. Materials are said to be inconsistent whenever $x=0.5$ and perfectly consistent whenever $x=1$. The discernment index takes real values on $z\in[0.5,1]$ with $z=0.5$ representing no discernment and $z=1$ representing perfect discernment.

For future reference we write the set from which consistency and discernment values can be chosen as $\mathcal{J}=\{(x,z):(x,z)\in[0.5,1]\times[0.5,1]\}$, which we refer to as Consistency-Discernment (CD) space. See Figure 1 for a depiction of $\mathcal{J}$, where the diagonal should be ignored for the moment. From the above it is clear that the unconditional probabilities for the signals are:

$$(1) \qquad P(a\,|\,z,x)=zx+(1-z)(1-x); \qquad P(b\,|\,z,x)=z(1-x)+(1-z)x.$$

Now apply Bayes' theorem to obtain signal-conditioned type discernment probabilities;

$$(2) \qquad P(A\,|\,a,z,x)=\frac{zx}{zx+(1-z)(1-x)}; \qquad P(B\,|\,b,z,x)=\frac{z(1-x)}{z(1-x)+(1-z)x}.$$

With $P(B\,|\,a,z,x)\equiv\overline{P}(A\,|\,a,z,x)\equiv 1-P(A\,|\,a,z,x)$, the complementary probabilities are defined as

$$(3) \qquad P(B\,|\,a,z,x)\equiv\overline{P}(A\,|\,a,z,x)=\frac{(1-z)(1-x)}{P(a\,|\,z,x)}; \qquad P(A\,|\,b,z,x)\equiv\overline{P}(B\,|\,b,z,x)=\frac{(1-z)x}{P(b\,|\,z,x)}.$$

Using variable subscripts to denote derivatives, the effects of consistency on the value of signal-conditioned discernment can be characterized as

$$(4) \qquad \begin{aligned} &P_x(A\,|\,a,z,x)=\frac{(1-z)z}{[P(a\,|\,z,x)]^2}\geq 0; && P_{xx}(A\,|\,a,z,x)=-\frac{2(1-z)(2z-1)z}{[P(a\,|\,z,x)]^3}\leq 0;\\ &P_x(B\,|\,b,z,x)=-\frac{(1-z)z}{[P(b\,|\,z,x)]^2}\leq 0; && P_{xx}(B\,|\,b,z,x)=\frac{2(1-z)z(2z-1)}{[P(b\,|\,z,x)]^3}\geq 0;\\ &P_{xz}(A\,|\,a,z,x)=\frac{1-x-z}{[P(a\,|\,z,x)]^3}\leq 0; && P_{xz}(B\,|\,b,z,x)=\frac{z-x}{[P(b\,|\,z,x)]^3}. \end{aligned}$$

Thus we have:

Remark 1. Given Premise 1, the effectiveness of signal

i) $s=a$ in predicting *A*, $P(A\,|\,a,z,x)$, is increasing and concave in the consistency index;

ii) $s=b$ in predicting *B*, $P(B\,|\,b,z,x)$, is decreasing and convex in the consistency index.

Discernment and consistency

iii) substitute in determining the effectiveness of signal $s = a$ as a predictor of *A;*

iv) substitute in determining the effectiveness of signal $s = b$ as a predictor of *B* whenever $x > z$ and complement whenever $x < z$.

The effect $P_x(A \mid a,z,x) \geq 0$ conveys that the share of *a* product which is really Type *A* increases with an increase in the overall share of materials that is the most prevalent type, *A*. The effect arises because, regardless of the z value, an increase in x reduces the amount of raw materials available to be incorrectly categorized as Type *A*. As for items *iii*)-*iv*), we will also encounter quantities $1 - x - z$ and $z - x$ at a later juncture. To better understand why $P_{xz}(B \mid b,z,x) \overset{\text{sign}}{=} z - x$, note that $P(B \mid b,z,x)$ is an average of the two types that signal $s = b$. By pointing to Type *B*, the signal points away from Type *A* and it can only do that by being more informative than the prior on Type *A*, namely x. The same reasoning can explain $P_{xz}(A \mid a,z,x) \overset{\text{sign}}{=} 1 - x - z \leq 0$ where of course the prior on non-prevalent Type *B*, $1 - x$, has been constrained to be less than 0.5.

We turn now to specifying the role of incentives in our model of signal information. We offer two related welfare metrics. One is expected dollar loss from mis-classification so that information has value to the extent that it more reliably guides actions away from loss-incurring decisions. The other is more general in that it assumes a difference in value for types. In order to explain the second metric we need some further notation. Prices for types *A* and *B* are given as, respectively, $R + \delta$ and R so that Type *A* carries a market premium whenever $\delta > 0$, and expected revenue is $(R + \delta) \times x + R \times (1 - x) = R + \delta x$. We will shortly develop an expression for expected loss due to mis-classification, $\mathcal{L}(z,x)$. Given this expression, expected profit is

(5) $$\pi(z,x) = R + \delta x - \mathcal{L}(z,x).$$

Our primary metric for evaluation is given by

Premise 2. The objective of the raw material's owner is to minimize the expected loss from mis-classification, $\mathcal{L}(z,x)$.

We focus on this objective because it offers fewer cases for evaluation. The obvious alternative is:

Premise 2'. The objective of the raw material's owner is to maximize expected profit, $\pi(z,x)$.

This objective offers more cases for evaluation. Even under Premise 2 fundamental discontinuities in choices will be shown to arise when minimizing expected loss. The possibility exists that corner solutions arising when minimizing expected loss from mis-classification when moving to Premise 2'. Having solved for, and provided insight on, the Premise 2 expected loss minimization problem we will devote a short section to extending the analysis to Premise 2'.

The loss, or value at risk, to the processor per unit of raw materials arising from an incorrect diagnosis on the part of the resource capacity, by either identifying *B* when the truth is *A* or *A* when the truth is *B*, is given as amount $\nu > 0$. This loss could arise due to inappropriate or problematic processing of these raw materials. If, for example, low-grade product is allocated to a materials pool that requires intensive processing that low-grade materials cannot support then throughput may decline and product may have to be discarded (Rasmussen 1968; Chandler 1992; Tamime and Law 2001). Alternatively, even when processing does not occur losses may arise because of poorly executed sorting such that consumer willingness to pay cannot be exploited (Miao and Hennessy 2015). An important feature of our initial loss characterization, which we will revisit, is that it is symmetric.

Premise 3A. Prices for types are common. Loss from assuming Type *B* when the material is Type *A* equals that from assuming Type *A* when the material is Type *B*.

Incentives enter the categorization problem as follows. Given $s = a$, when the resource takes the material as *B* (written as ta*B*) then expected loss to the processor is $\text{ELta}B = \nu P(A \mid a,z,x)$, see Figure 2. Alternatively, when the resource takes the material as *A* (ta*A*) for the same signal then expected loss to the processor is $\nu \overline{P}(A \mid a,z,x)$. With signal $s = a$ then the resource should be taken as *A* (henceforth referred to as or *a*ta*A*,) whenever $P(A \mid a,z,x) \geq 0.5$, i.e., from (2), $zx / [zx + (1-z)(1-x)] \geq 0.5$, so that the material $a$ta$A$ whenever $z \geq 1-x$.[7] In light of Premise 1, the condition always applies.

Remark 2. Given premises 1, 2 and 3A then $a$ta$A$ is always optimal.

The inference is intuitive in that Type A is prevalent. Absent further knowledge then one should assume product to be Type A. When there is further knowledge and it reinforces the prior knowledge then there is all the more reason to assume A. The inference is not so innocuous as it might seem, however, because it emerges from an expected profit calculation. Quite how robust this remark is to incentive assumptions made above will be explored in some depth later in this paper. The expected loss conditional on receiving signal $s = a$ is:

(6) $$L(a,z,x) = \nu P(B \mid a,z,x) = \frac{\nu(1-z)(1-x)}{zx + (1-z)(1-x)}.$$

Were the signal $s = b$ and the capacity assumes A then the expected loss to the processor would be $\nu P(B \mid b,z,x)$. Alternatively were the capacity receiving $s = b$ to assume B then the expected loss would be $\nu \overline{P}(B \mid b,z,x)$. With signal $s = b$ then the capacity should assume the material to be B whenever $\nu P(B \mid b,z,x) \geq \nu \overline{P}(B \mid b,z,x)$ which can be presented as $P(B \mid b,z,x) \geq 0.5$ and so as the condition $z(1-x)/[z(1-x)+(1-z)x] \geq 0.5$. Algebra shows that the factor will assume the material to be B whenever $z \geq x$. By contrast with the choice under the $s = a$ signal, this condition is not automatically met given our assumptions. That is, signal $s = b$ will be ignored whenever $z < x$. Remark 2 and subsequent observations on optimal signal use lead to

Remark 3. Given premises 1, 2 and 3A, whenever

i) $x \leq z$ then the resource capacity should take whichever signal $s \in \{a,b\}$ it observes;

ii) $z \in [0.5, x)$ then the resource capacity should assume type A regardless of signal observed.

Remark 3 conveys that whenever the discernment index exceeds the consistency index then

[7] Throughout the manuscript, when indifferent in terms of pecuniary reward we assume that the resource aligns with the signal.

discernment has utility. However, when raw materials consistency is sufficiently high then the dominant type will be assumed regardless, discernment has no utility and the product is a commodity according the terms of Definition 1. Figure 1 depicts our CD space where the boundary diagonal is allocated to differentiated product given the convention that a signal is accepted whenever there is indifference according to the expected loss criterion. An interesting model feature is that discernment and consistency have been rendered commensurable. The two can be placed on the same scale in part because types *A* and *B* are viewed as being symmetric except that *A* is the dominant type, but also in part because both are viewed as fractions of the time that an outcome emerges.

In light of Remark 3 the expression for signal-conditioned loss is more involved whenever $s=b$. Expected loss conditional on receiving $s=b$ is:

$$(7) \qquad L(b,z,x)=\begin{cases} \nu P(A\,|\,b,z,x)=\dfrac{\nu(1-z)x}{z(1-x)+(1-z)x} & \text{whenever } z\geq x \quad (\text{accept } b); \\ \nu P(B\,|\,b,z,x)=\dfrac{\nu z(1-x)}{z(1-x)+(1-z)x} & \text{whenever } z<x \quad (\text{ignore } b). \end{cases}$$

The expression may be written compactly as

$$(8) \qquad L(b,z,x)=\frac{\nu\min[x-zx,z-zx]}{z(1-x)+(1-z)x}=\frac{\nu\min[x,z]-\nu zx}{z(1-x)+(1-z)x}.$$

Next we consider the unconditional expected loss (UEL) across both signals received, given as the Bayesian Risk Function (Berger 1985):

$$(9) \qquad \begin{aligned} \mathcal{L}(z,x) &= P(a\,|\,z,x)L(a,z,x)+P(b\,|\,z,x)L(b,z,x) \\ &= \nu\times\begin{cases} 1-x & \text{whenever } z<x \quad (\text{ignore } b); \\ 1-z & \text{whenever } z\geq x \quad (\text{accept } b). \end{cases} \end{aligned}$$

This is the loss function that enters (5) above. Although conditional losses $L(a,z,x)$ and $L(b,z,x)$ are both continuously differentiable and non-linear in x and z, the unconditional loss function is piecewise linear. From (9) we have

Remark 4. Given premises 1, 2 and 3A, unconditional expected loss is

i) invariant to discernment level z whenever raw materials consistency is sufficiently large, i.e., $z<x$, and is decreasing in discernment level x otherwise;

ii) invariant to raw materials consistency x whenever capacity discernment z is sufficiently large, i.e., $z \geq x$, and is decreasing in raw materials consistency otherwise.

What does the above mean for how discernment and raw materials interact? Taking derivatives, and assuming the appropriate directional differentiability at the point of indifference, leads to

$$(10) \qquad \mathcal{L}_x(z,x) = \begin{cases} -\nu & \text{whenever } z < x; \\ 0 & \text{whenever } z \geq x. \end{cases} \qquad \mathcal{L}_z(z,x) = \begin{cases} 0 & \text{whenever } z < x; \\ -\nu & \text{whenever } z \geq x. \end{cases}$$

As one would expect, UEL is weakly decreasing with an increase in product consistency and also with an increase in capacity discernment. The information in (10) shows that the marginal value of x in reducing unconditional loss increases from 0 whenever $z > x$ to ν whenever $z < x$, while the marginal value of z is symmetric. In other words, raw materials consistency only becomes effective in reducing loss whenever it surpasses the discernment metric, and vice versa. For discernment to have value it must be used.

Proposition 1. Given premises 1, 2 and 3A, discernment and uniformity are perfect economic substitutes.

In Figure 3 the piecewise linear function commencing at $(0.5, \nu \times (1-x))$ and terminating at $(1,0)$ describes UEL as a function of discernment given both $s = b$ and a fixed consistency level. In light of the symmetry in (9) it is clear that the comparable function for consistency, but at a fixed discernment level, has the same form as UEL when $s = b$ as depicted in Figure 3.

Information Input Costs

As costly opportunities exist to increase consistency and discernment, we proceed by allowing the materials owner to trade off the costs and benefits of increasing the levels of each. Let raw materials with consistency x cost $r(x;\theta):[0.5,1]\times\mathbb{R}\rightarrow[0,\infty)$ where parameter θ indexes the state of technology regarding consistency. This function is held to be strictly positive, twice continuously differentiable, strictly increasing in x, and strictly decreasing in θ.[8] Furthermore, an increase in θ is held to reduce the marginal cost of procuring consistency level x, i.e., $r_{x\theta}(x;\theta)\le 0$. Let capacity with discernment level z receive competitive factor price $w(z;\lambda):[0.5,1]\times\mathbb{R}\to[0,\infty)$ where parameter λ indexes the state of technology regarding discernment. This function is also twice continuously differentiable. It is strictly increasing in z and strictly decreasing in λ while an increase in λ reduces the marginal cost of procuring discernment level z, i.e., $w_{z\lambda}(z;\lambda)\le 0$. Total cost is therefore

(11) $$C(z,x;\theta,\lambda)=r(x;\theta)+w(z;\lambda)+\boldsymbol{\mathcal{L}}(z,x),$$

with optimality conditions

(12) $$r_x(x;\theta)=\begin{cases}\nu & \text{whenever } z<x;\\ 0 & \text{whenever } z\ge x;\end{cases}\qquad w_z(z;\lambda)=\begin{cases}0 & \text{whenever } z<x;\\ \nu & \text{whenever } z\ge x.\end{cases}$$

It follows from Remark 4 and (12) that there is no incremental benefit to increasing materials consistency whenever $z\ge x$ so that whenever this is true then minimal effort, i.e., $x=0.5$, is put into ensuring consistency. Similarly, there is no incremental benefit to increasing factor discernment, i.e., $z=0.5$, whenever $z<x$. Thus the technology at issue is best-shot (Hirshleifer 1983) whereby whichever input, consistency or discernment, is viewed as being least effective is not considered. Therefore the cost specification as laid out in (11) may be partitioned in two, being $C(x\,|\,z;\theta,\lambda)|_{z=0.5}=$ $r(x;\theta)+w(z;\lambda)|_{z=0.5}+\boldsymbol{\mathcal{L}}(z,x)$ whenever there is consistency and an undiscerning resource and $C(z\,|\,x;\theta,\lambda)|_{x=0.5}=r(x;\theta)|_{x=0.5}+w(z;\lambda)+\boldsymbol{\mathcal{L}}(z,x)$ whenever there is discernment and inconsistent materials. The sub-problem solution sets are given as

(13) $$\begin{aligned} x^*(\theta)&=\arg\max\ C(x\,|\,z;\theta,\lambda)|_{z=0.5}, &&\text{(consistency, undiscerning resource);}\\ z^*(\lambda)&=\arg\max\ C(z\,|\,x;\theta,\lambda)|_{x=0.5}, &&\text{(discernment, inconsistent materials);}\end{aligned}$$

so that the unconditional solutions are given by the solution pair

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[8] Here it is assumed that greater consistency is to be attained by further increasing x. Consistency could also be promoted by shifting from x to below $1-x$. We will address incentives to shift toward the less prevalent product at a later juncture.

$$(14)\qquad (x^{**}(\theta), z^{**}(\lambda)) = \begin{cases} (x^{*}(\theta), 0) & \text{whenever } z^{*}(\lambda) < x^{*}(\theta); \\ (0, z^{*}(\lambda)) & \text{whenever } z^{*}(\lambda) \geq x^{*}(\theta). \end{cases}$$

The spliced upper curve in Figure 3 represents the total cost function, as in (11), when discernment is the choice and the optimal level of discernment, $z^{*}(\lambda)$, is also shown. There happens to be an interior solution, but this need not be the case. Figure 4 depicts the solution to (11) at a fixed minimal consistency level, which is given as the optimal, and as a function of discernment. In this case discernment is the more competitive approach and no effort is put into consistency.

Consider now what the θ and λ parameters can represent and how they can change. While the decision to use a technology is generally at a grower's discretion, for agriculture the availability of a technology is generally exogenous to the grower and it is technological availability that we seek to characterize with these parameters. The marginal cost of promoting consistency will decline with improvements in technology, including genetic technology that supports more reliable outputs. Other technical innovations that could improve raw materials consistency are pesticides such that product is closer to that under ideal production conditions. Technologies that reduce the risk of aflatoxin damage in corn, groundnuts, cotton and several other vulnerable crops are examples. In addition to Bt seed on corn (Wu 2006; Abbas et al. 2013) and cotton, such technologies can include cultivar development and fungicides (Mwakinyali 2019). Logistics such as the availability of identity-preserving containers can also act to foster consistency, as can both formal and informal institutions that facilitate contract enforcement (McLeod 2007).

As previously mentioned, the discernment technology might be labor-embodied as in the requisite Information Technology proficiencies (Kitchen et al. 2002; Erickson et al. 2018; Weersink et al. 2018). Alternatively the technology might be capital-embodied as with machine vision to sense physical properties when harvesting fruit (Burks et al. 2018) or an infra-red protein sorting technology (Miao and Hennessy 2015), see Figure 5. Which form an innovation takes might have drastic implications for factor requirements in a sector. The effect of a labor-embodied discernment shock could emerge from improved education, healthcare or nutrition, pushing marginal discernment costs down. Alternatively it could be as a result of competing demand for discernment capability in non-agricultural sectors, perhaps due to innovations elsewhere or to trade. Capital-embodied technologies might include vision hardware (Weiss and Biber 2011; Vázquez-Arellano et al. 2016), sensors to collect data on how types differ, software to process these data, and machines to act on processed data (Bechar and Vigneault 2016). Alternatively, breeding may be applied to devise a plant or animal that better allows capital to discern type differences (Tripodi 2018).

In order to develop the point we provide alternatives for $w(z;\lambda)$. Specify

(15) $$w(z;\lambda) \to w(z;\omega_L,\omega_K,\lambda_L,\lambda_K) = \min\left[\frac{\omega_L}{\lambda_L},\frac{\omega_K}{\lambda_K}\right]e(z),$$

where $e(z)$ is the increasing and convex generic cost of discernment, $\omega_L \geq 0$ and $\omega_K \geq 0$ index labor wages and capital rental costs, respectively, while $\lambda_L > 0$ and $\lambda_K > 0$ index the level of discernment innovation associated with respective factors. When $\omega_L / \lambda_L < \omega_K / \lambda_K$ then the labor source is chosen such that an increase in λ_L will have a non-increasing effect on demand for consistency and a non-decreasing effect on labor-embodied discernment. Thus how an innovation in the production of consistency affects demand for labor and capital in the process depends very much on how discernment is procured. In recent times the advent of smart machines (Davenport and Kirby 2016; Acemoglu and Restrepo 2018 a, b) suggests that capital may become the dominant source of discernment in processing and manufacturing, replacing labor and relieving demand for further technological improvements in consistency.

Loss Asymmetry

Here we relax Premise 3A to consider when the magnitude of loss from mis-categorizing differs by the form of mis-categorization. Green tomatoes may adversely affect the value of processed tomatoes by more than losing a perfect processing tomato, or the reverse may be true.

Premise 3B. Loss from assuming Type *B* when the material is Type *A* equals $v_A > 0$. Loss from assuming Type *A* when the material is Type *B* equals $v_B > 0$ where $v_A \leq v_B$.

For analytic convenience we specify $\tau = v_A / v_B > 0$. Whenever $\tau > 1$ then the cost of mis-categorizing Type *A* as Type *B* exceeds the cost of the converse tagging error. As Premise 3B asserts, we will place particular emphasis on $\tau \in [0,1)$ because in that case it is more important to keep Type *B* out of that held to be Type *A* than Type *A* out of that held to be Type *B*. In that sense Type *A* is held to be the more valuable so that the goal would be to increase Type *A* share in production, which is consistent with our modeling of $r(x;\theta)$.[9] We will study choices under each signal separately before integrating these choices such that incentives for consistency and discernment decisions can be developed.

Signal $s = a$

With this signal, when the factor assumes that the material is *B* then expected loss to the processor is $v_A P(A \mid a,z,x)$. Alternatively, when the factor assumes that the material is *A* then expected loss to the processor is $v_B \overline{P}(A \mid a,z,x)$. With signal $s = a$ then the factor should assume that the material is *A* whenever $(v_A + v_B)P(A \mid a,z,x) \geq v_B$ and so, from (2) above, should assume that the material is *A* whenever $zx / [zx + (1-z)(1-x)] \geq v_B / (v_A + v_B)$, which resolves to the *a*ta*A* condition,

(16) *a*ta*A*: $(\tau - 1)zx \geq 1 - z - x$.

Now the conditions in Premise 1 are only sufficient to ensure that *a*ta*A* is optimal whenever $\tau \geq 1$, i.e., whenever the loss from mis-categorizing *A* exceeds that from misclassifying *B*. Otherwise, remarks 1 through 3 do not apply. Consider when $z = x = 0.75$ so that (16) resolves to the weak inequality $\tau \geq 1/9$. Thus whenever $s = a$ is received and the loss from mis-categorizing *A* is at least one ninth that of mis-categorizing *B* then *A* should be assumed. However, when $\tau < 1/9$, i.e., $9v_A < v_B$, then the prevalence of Type *A* no longer suffices to ensure that $s = a$ is adequate evidence for designating the type as *A*. In other words, *a*-taken-as-*B* (*a*ta*B*) is expected profit maximizing.

In order to better understand decision-making under alternative discernment and consistency settings when $\tau \neq 1$, consider the value function $\mathcal{G}(\tau,z,x) = (\tau - 1)zx + z + x - 1$, from which we specify

[9] There is no reason why the more valuable type can't be less prevalent, and our model can be readily adapted to this context. Substantive insights will not change.

the threshold curve $\mathcal{G}(\tau,z,x)=0$. Notice the symmetry in x and z, $\mathcal{G}(\tau,z,x)=\mathcal{G}(\tau,x,z)$ as this symmetry carries over to curious symmetries that will be displayed when graphing the function. Points $(\tau,z,x)\in\overline{\mathbb{R}}^3_+$, i.e., in the nonnegative reals, such that $\mathcal{G}(\cdot)\geq 0$ are said to meet the *a*ta*A* threshold. Pertinent comparative statics are, $\mathcal{G}_z(\cdot)=(\tau-1)x+1\geq 0$, $\mathcal{G}_x(\cdot)=(\tau-1)z+1\geq 0$, and $\mathcal{G}_{xz}(\cdot)=\tau-1$. The cross derivative indicated the following:

Remark 5. Given premises 1, 2 and 3B then an increase in either discernment or consistency at least weakly decreases the level of the other needed to meet the *a*ta*A* threshold.

An alternative take on the $\mathcal{G}(\cdot)=0$ condition is to explicitly identify the threshold discernment and consistency levels for which *a*ta*A* applies:

(17) $$\hat{z}(x,\tau)=\frac{1-x}{1+(\tau-1)x}; \qquad \hat{x}(z,\tau)=\frac{1-z}{1+(\tau-1)z}.$$

For each threshold, any value above it satisfies *a*ta*A*. Threshold function limit values on $\mathcal{J}$ are

(18) $$\begin{aligned} &\hat{z}(x,\tau)|_{x=1}=0<0.5; \qquad \lim_{\tau\to 0}\hat{z}(x,\tau)=1; \qquad \hat{z}(x,\tau)|_{x=0.5}=\frac{1}{1+\tau}\in(0,1);\\ &\hat{x}(z,\tau)|_{z=1}=0<0.5; \qquad \lim_{\tau\to 0}\hat{x}(z,\tau)=1; \qquad \hat{x}(z,\tau)|_{z=0.5}=\frac{1}{1+\tau}\in(0,1). \end{aligned}$$

These evaluations show that when all materials are *A*, i.e., when $x=1$, then all discernment levels will support *a*ta*A*. The one exception, which we have ruled out in Premise 3B, is when $v_A=0$ so that $\tau=0$ and $\hat{z}(x,\tau)=1$ regardless of the $x\in[0.5,1]$ value. If Type *A* can be mis-classified as *B* without loss then *a*ta*A* is never optimal but whenever there is any loss at all then a consistency level sufficiently high will exist such that only minimal discernment is needed to support *a*ta*A*. In addition, when product is inconsistent, as with $x=0.5$, then discernment levels below $1/(1+\tau)$ should follow *a*ta*B*.

The downward sloping curve in Figure 6 uses (17) when evaluated at $\tau=0.5$ to divide $\mathcal{J}$ as follows:

(19) $$ataA:\ z\in\left[\max\left[0.5,1-\frac{x}{2-x}\right],1\right]; \qquad ataB:\ z\in\left[0.5,\max\left[0.5,1-\frac{x}{2-x}\right]\right).$$

Notice that *a*ta*A* threshold function $\hat{z}(x,\tau)|_{\tau=0.5}$ is decreasing and convex in x commencing at $(x,\hat{z})$

$=(0.5,0.\overline{6})$ and ending at $(x,\hat{z})=(0.\overline{6},0.5)$. In general we have $\hat{z}_x(\cdot)<0$, $\hat{z}_{xx}(\cdot)\le 0$ given $\tau\in(0,1)$, and $\hat{z}_\tau(\cdot)<0$. The first two derivatives show that the *a*ta*A* threshold discernment level is decreasing in the consistency index and is concave in the index whenever $\tau\in(0,1)$. The threshold declines at an accelerating rate because, given $\tau\in(0,1)$, an increase in consistency index x increases the cost of mis-categorizing Type *A* under signal $s=a$ by more than it increases the cost of mis-categorizing Type *B* under signal $s=a$. The third derivative shows that, for any consistency index value $x\in[0.5,1]$, the *a*ta*B* region contracts down toward the $z=0.5$ axis as $\tau\to 1$. From the symmetry shown in (17), the region also contracts toward the $x=0.5$ axis as $\tau\to 1$. Put simply, expected profit does not motivate taking $s=a$ as *B* when both *i*) the odds are stacked against the truth being *B*, as $x\in[0.5,1]$ and *ii*) the two mis-classification losses have similar values.

Remark 6. The set $(x,z)\subset\mathcal{J}$ such that *a*ta*B* is optimal contracts toward the point $(0.5,0.5)$ as $\tau\to 1$ and is empty whenever $\tau\ge 1$.

Notice that Figure 6 differs from Figure 1 because there is now a downward-sloping curve, generated by $s=a$, and also because the upward sloping curve no longer coincides with the main diagonal. As explained in Remark 6, when $\tau\to 1$ then the downward sloping curve vanishes. We turn now to the upward-sloping curve generated by $s=b$.

Signal $s=b$

With this signal, were the capacity to assume *A* then expected loss to the processor would be $\nu_B P(B\,|\,b,z,x)$. Alternatively were the resource receiving $s=b$ to assume *B* then expected loss would be $\nu_A \overline{P}(B\,|\,b,z,x)$. With signal $s=b$ then the resource should assume that the material is *B* whenever $\nu_B P(B\,|\,b,z,x)\ge \nu_A \overline{P}(B\,|\,b,z,x)$, i.e., whenever $P(B\,|\,b,z,x)\ge \nu_A/(\nu_A+\nu_B)$ and so whenever $z(1-x)/[z(1-x)+(1-z)x]\ge \nu_A/(\nu_A+\nu_B)$. Therefore, the factor will take the material to be *B* whenever the *b*ta*B* condition below is met and the following threshold is non-negative:

(20)
$$\begin{aligned} &b\text{ta}B: && (\tau-1)zx\ge x\tau-z;\\ &\text{Threshold:} && \mathcal{H}(\tau,z,x)=(\tau-1)zx-x\tau+z. \end{aligned}$$

When set equal to zero this threshold function is the increasing curve in Figure 6. Notice that $\mathcal{H}(\tau,z,x)|_{\tau=1}=z-x$ so that $\mathcal{H}(\tau,z,x)|_{\tau=1}=0$ is the diagonal line in Figure 1. By contrast with (16), $\mathcal{H}(\tau,z,x)-\mathcal{H}(\tau,x,z)\equiv(z-x)(1-\tau)\not\equiv 0$. Pertinent derivatives for $\mathcal{H}(\cdot)$ are as follows: $\mathcal{H}_z(\cdot)=(\tau-1)x+1\geq 0$, $\mathcal{H}_x(\cdot)=(\tau-1)z-1\leq 0$, and $\mathcal{H}_{xz}(\cdot)=\tau-1$. The $s=b$ analog to Remark 5 is then

Remark 7. Given premises 1, 2 and 3B, i.e., $\tau\in(0,1]$, an increase in either the discernment index or the consistency index at least weakly increases the minimum level of the other index needed to meet the *b*ta*B* threshold.

As with (16), threshold function (20) can be set to equal 0 and then specified alternatively as a dual pair of threshold functions:

(21) $\quad \overline{z}(x,\tau)=\dfrac{x\tau}{1+(\tau-1)x}; \qquad \overline{x}(z,\tau)=\dfrac{z}{\tau+(1-\tau)z};$

where any $z\in[\overline{z}(x,\tau),1]$ and any $x\in[0.5,\overline{x}(z,\tau))$ is in set *b*ta*B*. For $\overline{z}(x,\tau)$ the denominator is as in (17) but the numerator is increasing rather than decreasing in x while this numerator also involves the relative loss parameter. For $\overline{x}(z,\tau)$ the form differs markedly from that in (17). In addition to characterizing $\hat{z}(x,\tau)$, Figure 6 is also used to characterize $\overline{z}(x,\tau)$ in (21) when evaluated at $\tau=0.5$ to identify in the square $(x,z)\in\mathcal{J}$ the region where signal $s=b$ is rejected. The optimal choices are given as

(22) $\quad b\text{ta}B: \; z\in\left[\max\left[0.5,\dfrac{x}{2-x}\right],1\right]; \qquad b\text{ta}A: \; z\in\left[0.5,\max\left[0.5,\dfrac{x}{2-x}\right]\right).$

Threshold function $\overline{z}(x,\tau)$ is increasing and convex in x commencing at $(x,\overline{z})=(0.5,0.\overline{6})$ and ending at $(x,\overline{z})=(1,1)$.

Relevant comparative statics for (21) are: $\overline{z}_x(\cdot)>0$, $\overline{z}_{xx}(\cdot)\geq 0$, $\overline{z}_\tau(\cdot)\geq 0$. So the threshold discernment level for *b*ta*B* is increasing in the consistency index and is convex in the index whenever $\tau\in(0,1)$. The threshold increases with an increase in the relative loss parameter because an increase in τ is due to either an increase in ν_A, which is the penalty for mis-categorizing materials that are Type *A*, and/or a decrease in v_B, which is the penalty for mis-categorizing materials that are Type *B*. There is less incentive to reject signal $s=b$ whenever the penalty for doing so increases. From $\bar{x}(z,\tau)|_{z=0.5}=$ $1/(1+\tau)$ it can be seen that $\bar{x}(z,\tau)$ and $\hat{x}(z,\tau)$ coincide on the lower boundary of C-D space and that the 'Reject $s=b$' region vanishes as $\tau \to 0$. Again, there is less incentive to reject signal $s=b$ whenever the penalty for doing so decreases.

Remark 8. The set $(x,z)\subset \mathcal{J}$ such that *b*ta*A* is optimal contracts toward the line segment $[(1,0.5),(1,1)]$ as $\tau \to 0$. It converges toward $\mathcal{J}\cap\{x: x>z\}$ as $\tau \to 1$.

When viewed together, the *a*ta*A* and *b*ta*B* bounds reveal a dip toward the center in the 'product differentiation' subset of CD space. This reflects the concept that the value of information is greatest whenever decisions are marginal (Keppo et al. 2008). In this case decisions are marginal when $\tau<1$ and x is close to $1/(1+\tau)$. For $z=0.5$, so that there is essentially no information, then decisions are marginal whenever mean loss from going with Type *A* regardless of signal equals mean loss from going with Type *B* regardless of signal. The first mean loss is $v_A x$ while the second mean loss is $v_B(1-x)$ so that the marginal consistency level is $1/(1+\tau)$, as given previously.

Bounds and Loss Asymmetry

A final perspective on this pair of bounds is to consider how they change with the loss asymmetry parameter. So as to illustrate we take an horizontal section of CD space at $z=0.75$ and show how the bounds change with τ. The bound pair can then be written as

$$\text{(23)} \qquad \hat{x}(z,\tau)|_{z=0.75}=\frac{1}{1+3\tau}; \qquad \bar{x}(z,\tau)|_{z=0.75}=\frac{3}{3+\tau}.$$

The *a*ta*A* bound $\hat{x}(\cdot)|_{z=0.75}$ is decreasing and convex on $\tau\in[0,1]$ with extreme values on $(\tau,x)\in$ $[0,1]\times[0.5,1]$ at 1 for $\tau=0$ and 0.5 for $\tau=0.\overline{3}$. The *b*ta*B* bound $\bar{x}(\cdot)|_{z=0.75}$ is also decreasing and convex in $\tau\in[0,1]$ with extreme value at 1 for $\tau=0$, but with value 0.75 for $\tau=1$. Figure 7 depicts where $s=b$ is rejected. It is rejected at higher materials consistency levels because the prior, x, better disposes toward Type *A*, but only when losses are not very asymmetric as reflected by τ lower than but not far from 1 so that the loss from mis-categorizing Type *B* is not large. Similarly $s=a$ is rejected at lower τ values and lower consistency levels because then the likelihood of Type *A* is not so large and neither is the loss from mis-categorizing the type.

Synthesis

In light of remarks 6 and 8, the asymmetric loss version of Figure 1 can be provided as given in Figure 8. Given Definition 1, the material is a commodity whenever *i*) signal $s=a$ is always rejected, so that the product is assumed to be *B* in all cases, or *ii*) signal $s=b$ is always rejected so that the product is assumed to be *A* in all cases. Both cases become more likely whenever discernment is poor. In addition the former case occurs whenever consistency is low and v_A / v_B is low so that $1/(1+\tau)$ is close to 1, i.e., it is worse to assign Type *B* as Type *A* than vice versa. The latter occurs whenever consistency is high and v_A / v_B is close to 1 so that $1/(1+\tau)$ is close to 0.5 and one is likely to go with the prior rather than accept $s=b$. In both cases, information will have little value. Information has most value when the decision is marginal, i.e., consistency level is intermediate. Consider horizontal cross-sections of CD space.

Remark 9. Assume premises 1, 2 and 3B, 'commodity' as provided in Definition 1, *a*ta*A* consistency bound $\hat{x}(z,\tau)$ as given in (17) and *b*ta*B* consistency bound $\overline{x}(z,\tau)$ as given in (21). Then the materials are considered to be a commodity whenever either *i*) $z \in [1/(1+\tau),1]$ and $x \in (\overline{x}(z,\tau),1]$, or *ii*) $z \in [0,1/(1+\tau))$ and $x \in [0.5,\hat{x}(z,\tau)) \bigcup (\overline{x}(z,\tau),1]$.

We turn now to addressing how the pair (x,z) is chosen given asymmetric losses.

Incentives Under Asymmetric Losses

Consider now the loss functions in light of Figure 8. Cases *i*) and *ii*) in Remark 9 need to be treated separately. In Case *i*) then *a*ta*A* always applies. There is loss under *a*ta*A* whenever the materials are Type *B* and, from Premise 3B, loss is then $v_B > 0$. Expected loss conditional on $s=a$ is then as in (6) but for the value v_B. Signal $s=b$ may be rejected, however. It will be rejected whenever $x > \overline{x}(z,\tau)$.

Expected loss on receiving $s=b$ is:

$$(24)\qquad L(b,z,x)=\begin{cases}\nu_B P(B\,|\,b,z,x)=\dfrac{\nu_B z(1-x)}{z(1-x)+(1-z)x} & \text{whenever } x>\overline{x}(z,\tau) \quad \text{(ignore } b\text{);}\\ \nu_A P(A\,|\,b,z,x)=\dfrac{\nu_A (1-z)x}{z(1-x)+(1-z)x} & \text{whenever } x\le\overline{x}(z,\tau) \quad \text{(accept } b\text{).}\end{cases}$$

The expression may be written compactly as

$$(25)\qquad L(b,z,x)=\frac{[1+(\tau-1)x]\nu_B\min[z,\overline{z}(x,\tau)]-\nu_A zx}{z(1-x)+(1-z)x}.$$

The UEL across both signals received is then:

$$(26)\qquad \begin{aligned}\mathcal{L}(z,x)&=P(a\,|\,z,x)L(a,z,x)+P(b\,|\,z,x)L(b,z,x)\\ &=\nu_B\times\{1-z-x+(1-\tau)zx+[1+(\tau-1)x]\min[z,\overline{z}(x,\tau)]\}\\ &=\nu_B\times\begin{cases}1-x & \text{whenever } x>\overline{x}(z,\tau) \quad \text{(ignore } b\text{);}\\ [1-(1-\tau)x](1-z) & \text{whenever } x\le\overline{x}(z,\tau) \quad \text{(accept } b\text{).}\end{cases}\end{aligned}$$

From (26) we have

$$(27)\qquad \mathcal{L}_z(z,x)=\begin{cases}0 & \text{whenever } x>\overline{x}(z,\tau) \quad \text{(ignore } b\text{);}\\ -\nu_B\times[1-(1-\tau)x] & \text{whenever } x\le\overline{x}(z,\tau) \quad \text{(accept } b\text{).}\end{cases}$$

Figure 9 describes $\mathcal{L}(\cdot)$ as a function of z where $\tau\in(0,1)$ (solid line) and compares it with $\mathcal{L}(\cdot)$ as a function of z in (9) where $\tau=1$ (broken line extensions). We know from (21) and (26) that all of the following apply: $\overline{z}(\cdot)<x$, $\mathcal{L}_x(\cdot)=-\nu_B\times[1-(1-\tau)x]>-\nu_B$ on $z\in(\overline{z}(\cdot),1)$, and $\mathcal{L}(z,x)=0$ whenever $z=1$. The loss function for given consistency level is depicted in solid for a value $\tau\in(0,1)$ and is depicted as broken lines for $\tau=1$ where the two coincide whenever $z\in[0,\overline{z}(\cdot)]$.

In Case *ii*) then *a*ta*A* need not apply and so $L(a,z,x)$ needs to be adapted. Expected loss conditional on $s=a$ is then:

$$(28)\qquad L(a,z,x)=\begin{cases}\nu_A P(A\,|\,a,z,x)=\dfrac{\nu_A zx}{zx+(1-z)(1-x)} & \text{whenever } x<\hat{x}(z,\tau) \quad \text{(ignore } a\text{);}\\ \nu_B P(B\,|\,a,z,x)=\dfrac{\nu_B (1-z)(1-x)}{zx+(1-z)(1-x)} & \text{whenever } x\ge\hat{x}(z,\tau) \quad \text{(accept } a\text{).}\end{cases}$$

The expression may be written compactly as

$$(29)\qquad L(a,z,x)=\frac{[1+(\tau-1)x]\nu_B\min[\hat{z}(x,\tau),z]}{zx+(1-z)(1-x)}-\frac{\nu_B(1-x)z}{zx+(1-z)(1-x)}.$$

The UEL across both signals received is then:

$$(30)\qquad \begin{aligned}\mathcal{L}(z,x)&=P(a\,|\,z,x)L(a,z,x)+P(b\,|\,z,x)L(b,z,x)\\ &=\nu_B\times\begin{cases}\tau x & \text{whenever } x<\hat{x}(z,\tau) \quad \text{(ignore } a\text{);}\\ [1+(\tau-1)x](1-z) & \text{whenever } x\in[\hat{x}(z,\tau),\overline{x}(z,\tau)] \quad \text{(accept both signals);}\\ 1-x & \text{whenever } x>\overline{x}(z,\tau) \quad \text{(ignore } b\text{).}\end{cases}\end{aligned}$$

Figure 10 depicts UEL as a function of x and at different z values where the observations $\overline{x}_z(\cdot)>0>\hat{x}_z(\cdot)$ have been applied. UEL is provided at two discernment levels, z_0 (three connected unbroken lines) and z_1 (connected unbroken lines except on $x\in(\hat{x}(z),\overline{x}(z))$) where $z_0<z_1$. For both curves, UEL increases in the low consistency region, where $s=a$ is rejected, and decreases in the high consistency region, where $s=b$ is rejected. In between it decreases because the loss from mis-categorizing Type *B*, declines faster than the rise in loss from mis-categorizing Type *A* as Type *A* becomes more prevalent. Notice too that, for $z=z_0$, $\mathcal{L}_x(\cdot)=(\tau-1)(1-z_0)\le 0$ on $x\in(\hat{x}(z),\overline{x}(z))$ and $\mathcal{L}_x(\cdot)=-1<(\tau-1)(1-z_0)<0$ on $x\in(\overline{x}(z),1)$.

Remark 10. Given premises 1, 2 and 3B, increasing marginal returns to consistency arise when consistency shifts from the region where both signals are accepted to the region where $s=b$ is rejected.

Given increasing marginal returns, we cannot be sure that comparative statics for x, or indeed z for that matter, are continuous. We now compare the broken and unbroken UEL curves in Figure 10. It is clear that greater discernment pushes down UEL but only where both signals are accepted. From (30) we can see that the UEL marginal response to the discernment index is

$$(31)\qquad \mathcal{L}_z(z,x)=\nu_B\times\begin{cases}0 & \text{whenever } x<\hat{x}(z,\tau) \quad \text{(ignore } a\text{);}\\ -[1+(\tau-1)x] & \text{whenever } x\in[\hat{x}(z,\tau),\overline{x}(z,\tau)] \quad \text{(accept both signals);}\\ 0 & \text{whenever } x>\overline{x}(z,\tau) \quad \text{(ignore } b\text{);}\end{cases}$$

as depicted in Figure 11. As consistency increases discernment commences having a beneficial impact and then ceases having a beneficial impact.

Proposition 2. Given premises 1, 2 and 3B, discernment and uniformity are

i) economic substitutes whenever $z \in [1/(1+\tau),1]$;

ii) economic complements at low consistency levels and economic substitutes at high consistency levels whenever $z \in [0,1/(1+\tau))$.

Increasing returns and also the switch in complementarity status show that comparative static responses to a marginal cost reduction in consistency or in discernment, as reflected by lower θ or λ respectively, are complex. One can, however, work through effects rather informally by way of (30) and Figure 10. Consider when $\tau < 1$ and λ is low with high marginal costs of discernment. The initial situation is for rejection of one signal and assumption that type is either *B*, for $x < 1/(1+\tau)$, or *A* otherwise. However λ increases over time and at a certain level, brought on presumably by developments largely external to agriculture and food production, a threshold is breached such that it is economic to use the signal. The result is an increase in demand for both discernment and consistency whenever $x < 1/(1+\tau)$ and an increase in demand for discernment but decrease in demand for consistency whenever $x \geq 1/(1+\tau)$. And there the story ends. Any further increase in λ will have no further effect.

Alternatively consider when the initial situation is for rejection of $s = a$ and the assumption that type is *B*, but now let θ increase over time to reduce the marginal cost of consistency. This can cause what we refer to as the Slingshot effect.[10] At some point as θ increases the shift to 'Accept both' occurs, increasing demand for both z and x through complementarity. As θ increases further then 'Reject *b*' becomes optimal and there is no further need for discernment. But the withdrawal of discernment further increases demand for consistency because the two inputs are now substitutes. The entry of and subsequent withdrawal of discernment both increase demand for consistency. Figure 12 depicts the situation. More generally we can write

[10] In astrophysics, an object can be first drawn toward a planet but then propelled out at accelerated speed due to centrifugal force.

Proposition 3. Given premises 1, 2 and 3B, any decline in the marginal cost of

i) discernment promotes product differentiation

ii) consistency promotes product differentiation whenever consistency and discernment are both sufficiently low but promotes commodity production whenever consistency is sufficiently high but discernment is sufficiently low.

While results to this point have addressed only expected loss minimization, we have pointed out that increased consistency may also have positive or negative gross revenue implications. In what follows we allow for this so as to provide guidance on how to modify results if need be.

Incentives Under Asymmetric Type Prices

When type prices are allowed to differ then we must think of an expected profit maximization problem rather than of just an expected loss minimization problem. Given (5) and (31), expected profit in the presence of Case *ii*) losses is

$$(32)\qquad \mathcal{R}(z,x) = P + \delta x - \nu_B \times \begin{cases} \tau x & \text{whenever } x < \hat{x}(z,\tau); \\ [1+(\tau-1)x](1-z) & \text{whenever } x \in [\hat{x}(z,\tau), \overline{x}(z,\tau)]; \\ 1-x & \text{whenever } x > \overline{x}(z,\tau). \end{cases}$$

One way of thinking about choice over (x,z) in the above is that the curve in Figure 10 is adjusted by $P + \delta x$, be it an increasing or decreasing line. The marginal impact is

$$(33)\qquad \mathcal{R}_x(z,x) = \delta - \begin{cases} \nu_A & \text{whenever } x < \hat{x}(z,\tau); \\ (\nu_A - \nu_B)(1-z) & \text{whenever } x \in (\hat{x}(z,\tau), \overline{x}(z,\tau)); \\ -\nu_B & \text{whenever } x > \overline{x}(z,\tau). \end{cases}$$

If $\delta > \nu_A$ then marginal revenue from increasing consistency will always be positive and increasing, leading to the possibility of plural local optima to the revenue less cost problem. If $\delta < -\nu_B$ then marginal revenue decreases in x, indicating that incurring positive marginal costs cannot be justified and market preference for Type *B* is encouraging $x \in [0, 0.5]$.

Introducing Switching Costs

We turn now to acknowledging the second effect that we see in automation, namely reducing the costs of making adjustments. In measurement applications, the digital revolution has involved electronics substituting for mechanical processes where earlier analog devices manipulated more energy intensive physical representations of a problem. As an extreme example, in the automation of processed tomato harvesting color sensors eventually replaced human sorters. The Internet of Things may reduce costs further by placing some of the equipment needed for switching and sorting into remote scale-efficient locations.

Our baseline model is that of a railway switch whereby product differentiation requires that product signaling as a given type are directed to a given station, *A* or *B*, see Figure 13. One can leave the switch in place, directing materials to the upper line, at no cost. Alternatively, one can use the sensor and switch at cost κ per change of switch position. By allowing changes of state, adjustment costs introduce dynamic considerations into signal response problems. When choosing to incur such costs one needs to establish whether the new machine state will incur further costs going forward. In infinite horizon this is a complicated problem that would require analysis of the appropriate Hamilton-Jacobi-Bellman equation (Brekke and Øksendal 1994; Song et al. 2011). So as to illustrate the implications but in a concise and tractable way we will consider a finite T -period problem while assuming common prices and mis-categorization costs for types, i.e., $\delta = 0$ and $\nu_A = \nu_B = \nu$.

Incremental cost $\kappa \in [0, \nu)$ is incurred whenever a switch occurs. Given that there are transition costs, initial position now matters. In Period *T* the position is either $c = A$ or $c = B$. We need to consider each of the four combinations $(c, s) \in \{A, B\} \times \{a, b\}$. For each we then need to establish the decision rule for choices made at Period T conditional on Period $T-1$ state $c \in \{A, B\}$.

When in A

Action thresholds need to be considered for both signals. We will show below that the threshold for $s = a$ is trivial while that for $s = b$ depends on sorting costs.

When $(c, s) = (A, a)$**:** When the capacity assumes the material to be *B*, requiring expenditure on a position switch, then expected loss to the processor is $\nu P(A|a,z,x)+\kappa$. Alternatively, when the capacity assumes that the material is *A* then expected loss to the processor is $\nu \overline{P}(A|a,z,x)$. The switch will occur only when $\nu \overline{P}(A|a,z,x) > \nu P(A|a,z,x)+\kappa$, i.e., when $z < G^{A,a}(x,\kappa) \equiv (\nu-\kappa)(1-x)/(\nu-\kappa+2\kappa x)$ which will never apply given that $(x,z) \subset \mathcal{J}$.

When $(c,s)=(A,b)$**:** When the capacity assumes the material to be *B*, then a position switch occurs and expected loss to the processor is $\nu P(A|b,z,x)+\kappa$. Alternatively, when the capacity assumes *A* then expected loss to the processor is $\nu \overline{P}(A|b,z,x)$. The switch will occur when $\nu \overline{P}(A|b,z,x) > \nu P(A|b,z,x)+\kappa$, i.e., when $z \geq G^{A,b}(x,\kappa) \equiv (\nu+\kappa)x/(\nu-\kappa+2\kappa x)$ and there will be inertia otherwise. Now evaluations of $G^{A,b}(x,\kappa)$ at the limit points of $x \in [0.5,1]$ and of $\kappa \in [0,\nu)$ are $G^{A,b}(\cdot)|_{x=0.5} \equiv 0.5(\nu+\kappa)/\nu \in [0.5,1)$, $G^{A,b}(\cdot)|_{x=1} \equiv 1$, $G^{A,b}(\cdot)|_{\kappa=0} \equiv x$, $G^{A,b}(\cdot)|_{\kappa=\nu} \equiv 1$, and furthermore the set bound $x \in [0.5,1]$ ensures that $z/x \geq G^{A,b}(x,\kappa)/x \equiv (\nu+\kappa)/(\nu-\kappa+2\kappa x) \geq 1$. Therefore the bound resides entirely on or above the diagonal in CD space.

Bound derivatives can be shown to satisfy $G_x^{A,b}(\cdot) > 0$, $G_{xx}^{A,b}(\cdot) < 0$, and $G_\kappa^{A,b}(\cdot) \geq 0$ so that the bound increases, but at a decreasing rate, as materials consistency increases while it shifts upward as sorting costs increase. Figure 14, which should be contrasted with Figure 1, depicts the inertial bounds for lower (solid curve for κ_1) and higher (broken curve for $\kappa_2 > \kappa_1$) values of κ. In it the map $(A,b) \rightarrow A$ declares that the state does not change under *b*. The bound is what is referred to as the Marshallian bound (Dixit 1989). Were we modelling a stage earlier than the last, such that state *A* might need to be revisited later, then uncertainty induced inertia (hysteresis) would apply and the bound delimiting the minimal discernment level for $s=b$ to be used would be even higher than $G^{A,b}(\cdot)$.

When in B

We will show below that, by contrast with being in Period $T-1$ state *A*, neither bound is trivial when in Period $T-1$ state *B*.

When $(c,s)=(B,a)$**:** When the capacity assumes *B* then expected loss to the processor is $\nu P(A|a,z,x)$. Alternatively, when the capacity assumes *A* then expected loss to the processor is

$\nu\overline{P}(A\,|\,a,z,x)+\kappa$. The switch will occur when $\nu P(A\,|\,a,z,x)\geq\nu\overline{P}(A\,|\,a,z,x)+\kappa$, i.e., when $z\geq G^{B,a}(x,\kappa)\equiv(\nu+\kappa)(1-x)/(\nu+\kappa-2\kappa x)$. Here bounds on $\mathcal{J}$ are $G^{B,a}(\cdot)|_{x=0.5}\equiv0.5+0.5\kappa/\nu\in[0.5,1)$, $G^{B,a}(\cdot)|_{x=1}\equiv0$, $G^{B,a}(\cdot)|_{\kappa=0}\equiv1-x$, and also $G^{B,a}(\cdot)|_{\kappa=\nu}\equiv1$ whenever $x<1$. By contrast with $(c,s)=(A,a)$ the condition is not always satisfied. The bound is depicted as the downward sloping curve in Figure 15 positioned toward the CD space vertex $(0.5,0.5)$ where the calculations $G_x^{B,a}(\cdot)<0$, $G_{xx}^{B,a}(\cdot)<0$, and $G_\kappa^{B,a}(\cdot)\geq0$ clarify both boundary shape area expanding effect of switching costs.

When $(c,s)=(B,b)$**:** When the capacity assumes *B* then expected loss to the processor is $\nu P(A\,|\,b,z,x)$. Alternatively, when the capacity assumes *A* then expected loss to the processor is $\nu\overline{P}(A\,|\,b,z,x)+\kappa$. The switch will occur when $\nu P(A\,|\,b,z,x)\geq\nu\overline{P}(A\,|\,b,z,x)+\kappa$, i.e., when $(\nu-\kappa)x/(\nu+\kappa-2\kappa x)\geq z\equiv G^{B,b}(\cdot)$. Switching out of *B* only occurs whenever signal discernment is sufficiently poor. Here bounds on $\mathcal{J}$ are $G^{B,b}(\cdot)|_{x=0.5}\equiv0.5-0.5\kappa/\nu\in[0,0.5)$, $G^{B,b}(\cdot)|_{x=1}\equiv1$, $G^{B,b}(\cdot)|_{\kappa=0}\equiv x$ and also $G^{B,b}(\cdot)|_{\kappa=\nu}\equiv0$ whenever $x<1$. As $G_x^{B,b}(\cdot)>0$, $G_{xx}^{B,b}(\cdot)>0$, and $G_\kappa^{B,b}(\cdot)\leq0$, the bound is increasing and convex but declines as sorting costs increase. Bound $G^{B,b}(\cdot)$ is also provided in Figure 15. Note the similarity with Figure 6, due to the fact that a differential in loss can be viewed as a cost to switching into that state.

Figure 16 summarizes transition dynamics. Each of the four regions reflects different phenomena. The regions corresponding to the upper and lower diagonal regions, respectively, in Figure 1 are also above and below the diagonal, but in each case contracted. At upper left corner, where discernment is high and consistency low, switching costs are incurred in each state and the result is differentiated product. At lower right corner, where discernment is comparatively low and consistency high then the prior dominates, Type *A* is assumed regardless of signal and there is no incentive to invest in discernment.

Relative to Figure 1 the two new regions are *i*) a convex neighborhood of $(0.5,0.5)$ when intersected with $\mathcal{J}$, and *ii*) around the diagonal but with the neighborhood of $(0.5,0.5)$ removed and so a non-convex set. For the convex set, transactions costs dominate regardless of signal, there is complete state inertia and no incentive to invest in discernment. The non-convex region is most interesting because there the signal is followed when in state *B* but there is inertia when in *A*. In the stochastic process sense this is an absorbing state (Bhattacharya and Waymire 1990). Once $s = a$ is observed then there is transition into state *A*, never to leave and so the firm will not make the investment in discernment to distinguish between types. Were we to move far from the terminal state then this non-convex region would only expand as processors also factor in the cost of future switches were a switch to be made now. Figure 16 also summarizes our findings. Three of four regions generate a commodity outcome, the cause being some combination of Type *A* prevalence, poor discernment and switching costs. Only the upper left region defined by vertex set $\{(0.5,1),(0.5,(\nu+\kappa)/(2\nu)),(1,1)\}$ supports differentiated product and so supports investment in discernment. This region will expand as $\kappa \to 0$.

Proposition 4. Given premises 1, 2 and 3B, and switching frictions, a reduction in sorting costs expands the product differentiation set under Marshallian bounds and increases the incentive to invest in discernment.

The proposition is in accord with Proposition 3 in that both show information technology innovations to promote both discernment and product differentiation. Less clear is the effect on incentives to produce consistent product. Whenever discernment and consistency complement then the effect of lower sorting costs is likely to boost investment in consistency. However whenever consistency is already high then there may be little effect or incentive to reduce investment in consistency because in such cases discernment acts as a substitute.

Conclusion

The purpose of this paper has been to develop upon how information innovations are affecting production processes in the agricultural and food sectors. Our workhorse when doing so has been Bayes' rule with raw materials consistency providing the prior and discernment, likely through sensors, providing case-by-case posteriors upon which production and transformation decisions can be conditioned. The context has been on sorting produce, but applications include any setting in which real-time information measurement devices are used.

One potential non-produce application that has been the subject of much research in recent years is weed identification with intent to spot-spray, where each crop presents it unique challenges (Nieuwenhuizen et al. 2010; Lottes 2017). The goal there is to sense the presence or absence of weeds in real-time so as to trade off two types of loss as we have done. One is yield loss, avoided through heavy dosage on identified weeds, while the other is unnecessary herbicide use, avoided when the signal correctly discerns the absence of any controllable weed. Given that some herbicides, such as atrazine, are recognized as potentially harmful to the environment and to human health, the technology could assist in reducing social damage and in providing a management plan other than removal from the market. Information technologists recognized early the merits of Bayesian decision analysis for implementing such systems (Tellaeche et al. 2008) but have not, so far as we know, related these signal conditioned choices to economic incentives.

We do not claim that the effects we model capture the universe of impacts that these technologies will have on agriculture. In none of our work, for example, do we address externalities that might include environmental, food safety and worker safety monitoring (Weersink et al. 2018; Finger et al. 2019), or insurance moral hazard (Yu and Hendricks 2010). These issues deserve their own analyses. But we do think that our model can prove useful in framing the issues, where consistency in our model is a primitive representation of decision context complexity, discernment reflects extent of rationality or cognitive competency and incentives are provided by signal conditioned losses. We also see potential for using the model to integrate economic costs and benefits into the Bayesian information processing procedures that will likely make real-time management decisions in automated devices. A further possibility is to explore the use of real-time sensor data and prior knowledge about environmental effects so as to include signal-conditioned Pigouvian subsidies when decision benefits and costs are calculated as inputs into real-time Bayesian decision models for robotic choices.

Although the model does not address data control and ownership issues we think that it can be adapted to these ends. Consider the weighty issues of farm organizational form. As Poppe et al. (2015) have argued, information technology may remove barriers to labor division at the farm level (Allen and Lueck 1998, 2004). Here the multi-tasking owner-operator emerges as a better farmer than a corporation supervising employees because the decision environment is insufficiently consistent and owner-operators are better able to discern signals than are more remote managers. Owner-operators have better discernment, which is highly valued when there are many decisions to be made. The remote manager likely can deliver scale economies. Other parts of the modern economy are facing similar economic forces, where franchised retailing and home services are examples. There some actions are taken locally and some are centralized, where labor supervision and local marketing are typical examples of the former while materials procurement and mass media marketing are typical examples of the latter. Perhaps field cropping is about to follow much of animal agriculture in this regard, where genetics, feed and marketing are often centralized while labor, manure disposal and other decisions are local? After automation replaces many labor tasks with capital, but keeps the owner-operator in place, perhaps the next phase will involve replacing the owner-operator with centralized management, or at least centralization of those managerial functions for which local discernment is no better than remote discernment?

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Table 1. Probabilities in Identifying Raw Materials Type from Signal

If type is	then signal is $s=a$ with probability	then signal is $s=b$ with probability
A	z	$1-z$
B	$1-z$	z

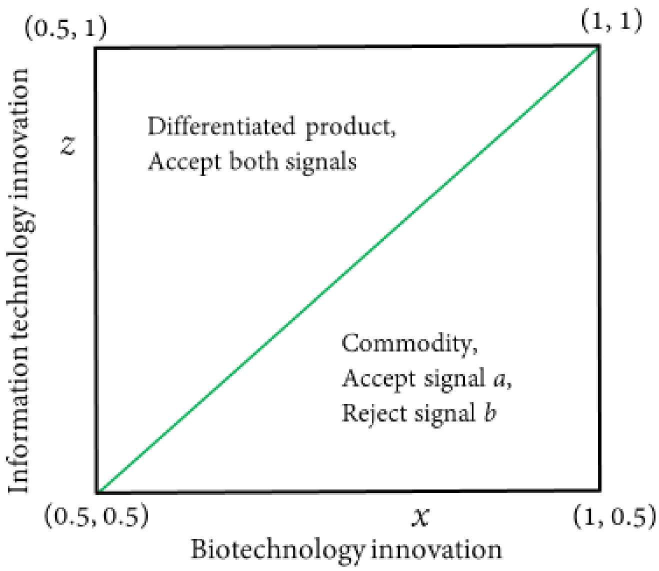

Figure 1. Commodity and differentiated product as functions of consistency and discernment

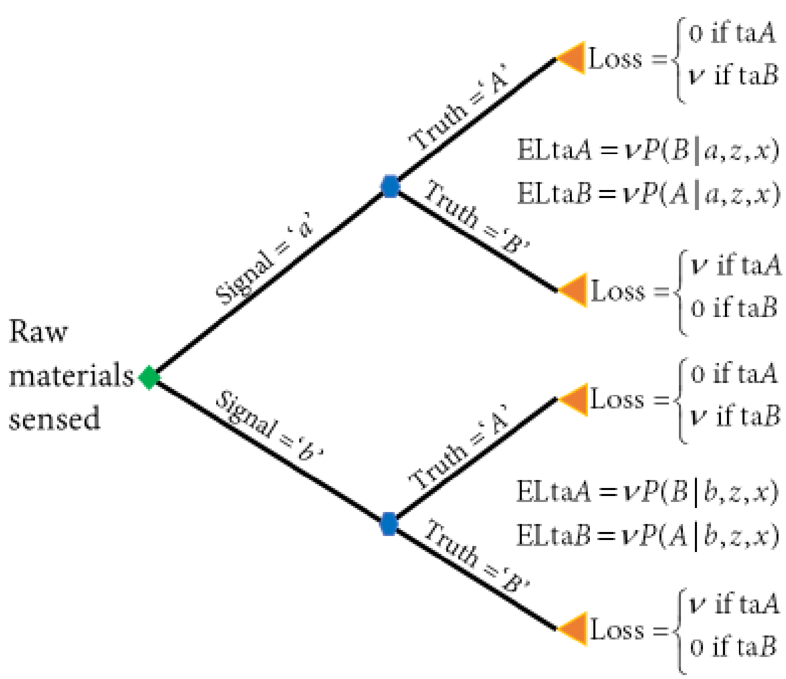

Figure 2. Characterizing signals and losses

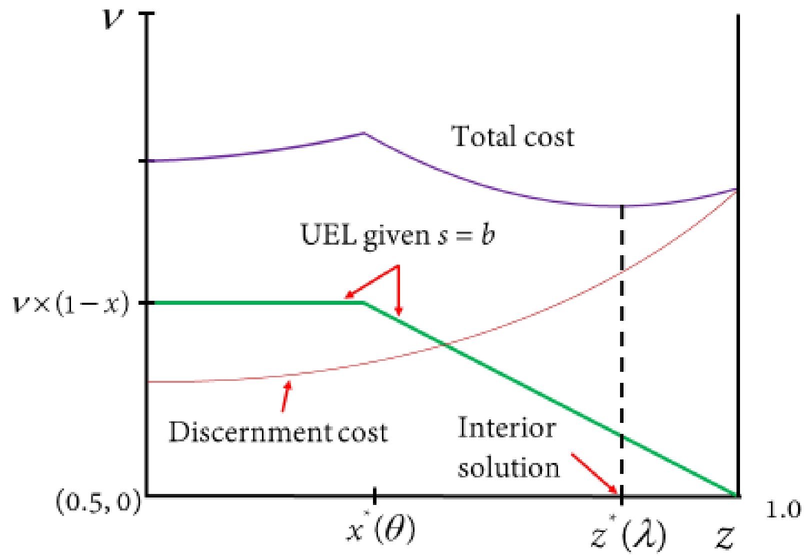

Figure 3. Total cost as a function of discernment parameter *z*

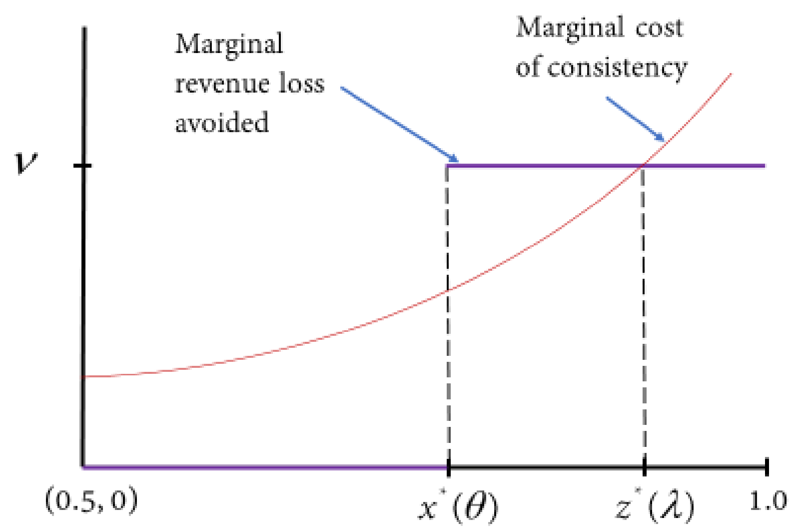

Figure 4. Marginal analysis to determine optimal discernment choice

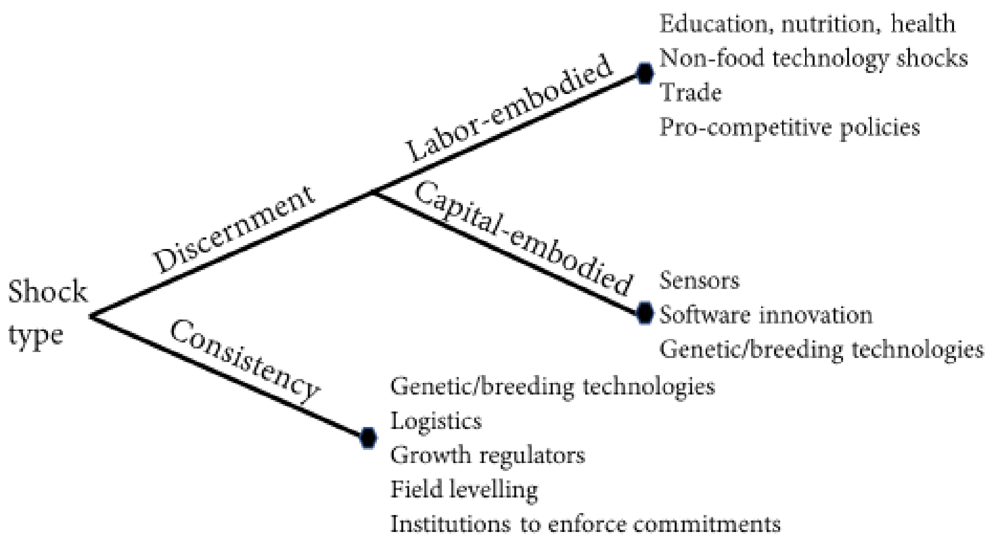

Figure 5. Schema for shocks to marginal costs of consistency and discernment, as inputs into food production

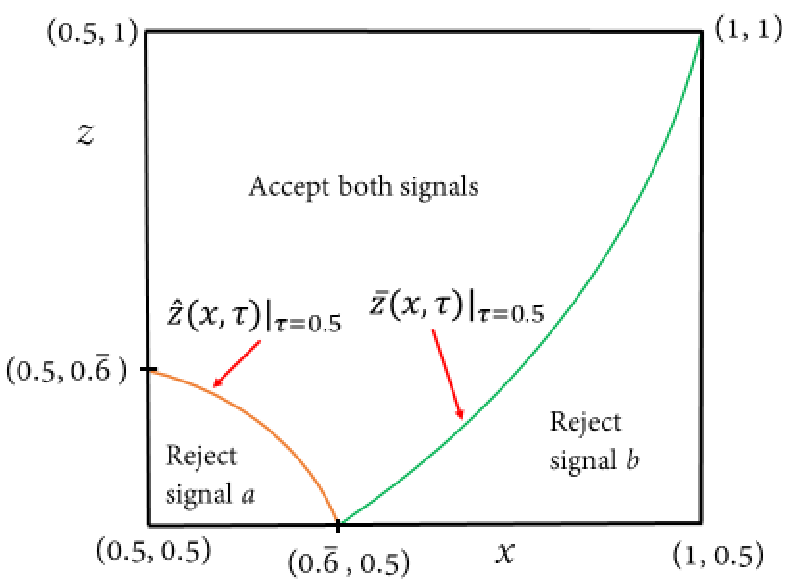

Figure 6. Regions where signals are accepted and rejected, when $\tau = 0.5$

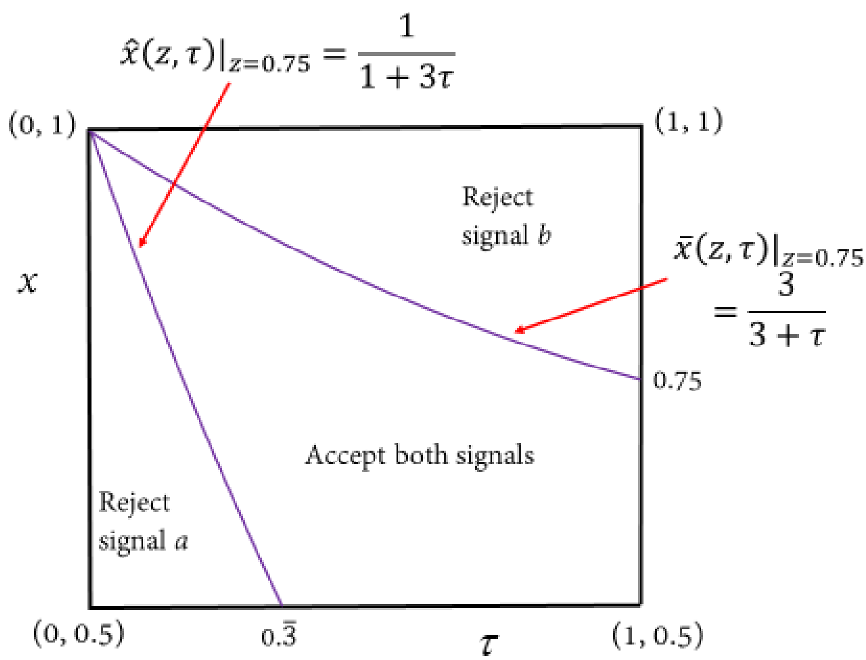

Figure 7. Commodities, consistency and loss asymmetry, $z = 0.75$ assumed

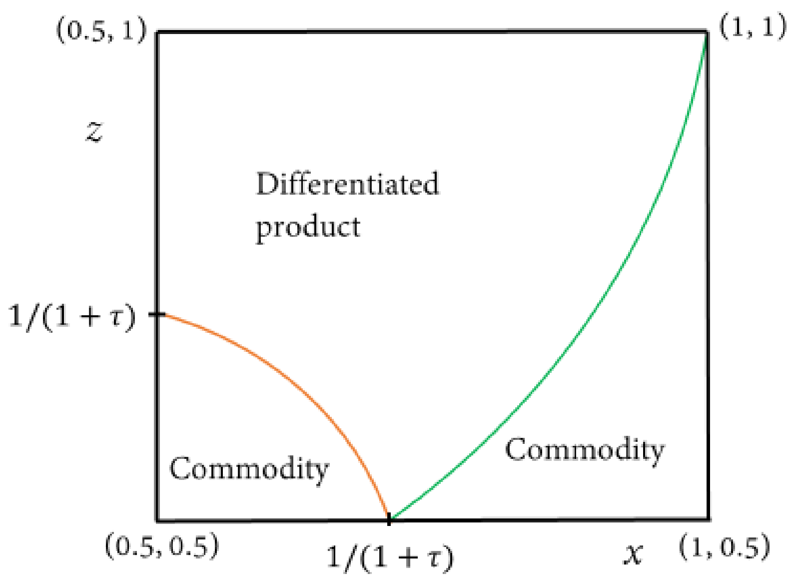

Figure 8. Commodities and differentiated product in CD space

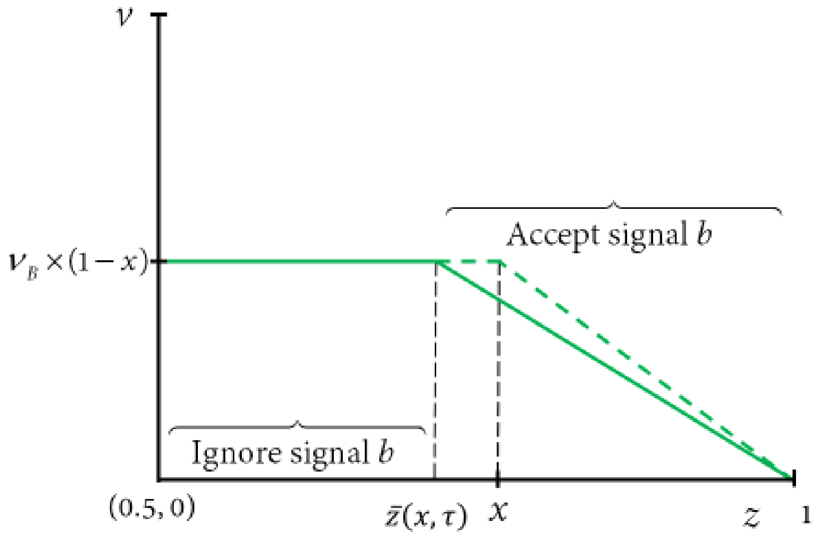

Figure 9. Unconditional Expected Loss as a function of discernment parameter *z*, for symmetric losses and also for when mis-categorizing *A* is lower than that when mis-categorizing *B*

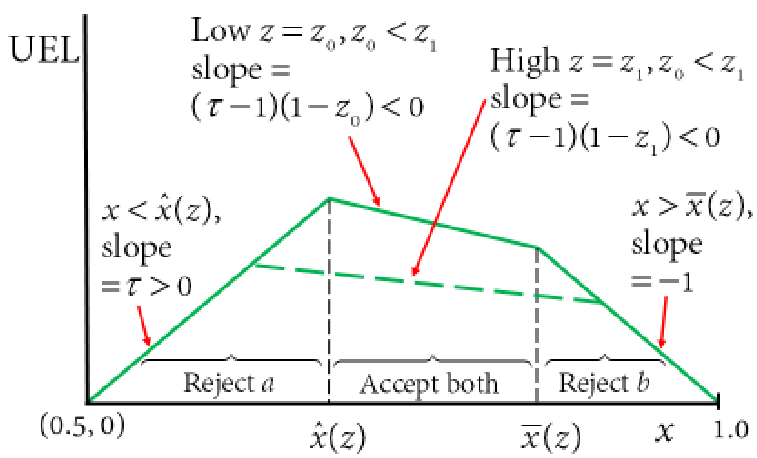

Figure 10. Unconditional Expected Loss as a function of consistency parameter *x*; Case of asymmetric loss

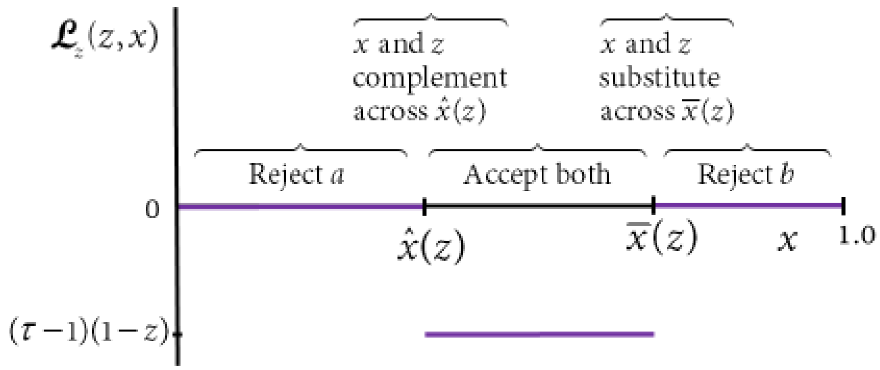

Figure 11. Unconditional Expected Loss marginal response to discernment at different consistency levels

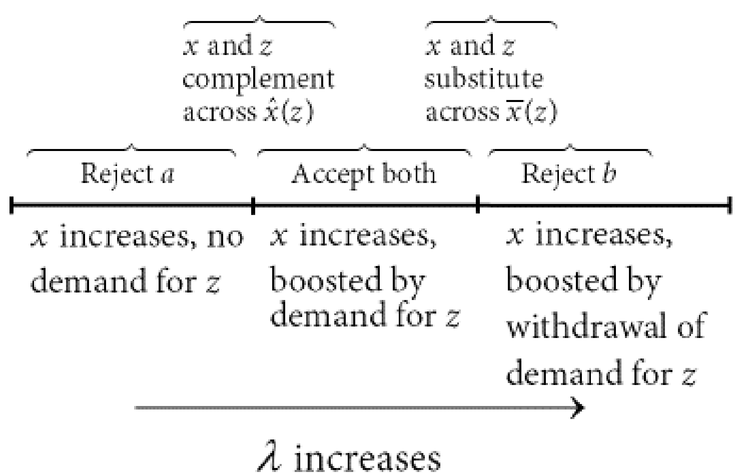

Figure 12. Slingshot effect as marginal cost of consistency declines

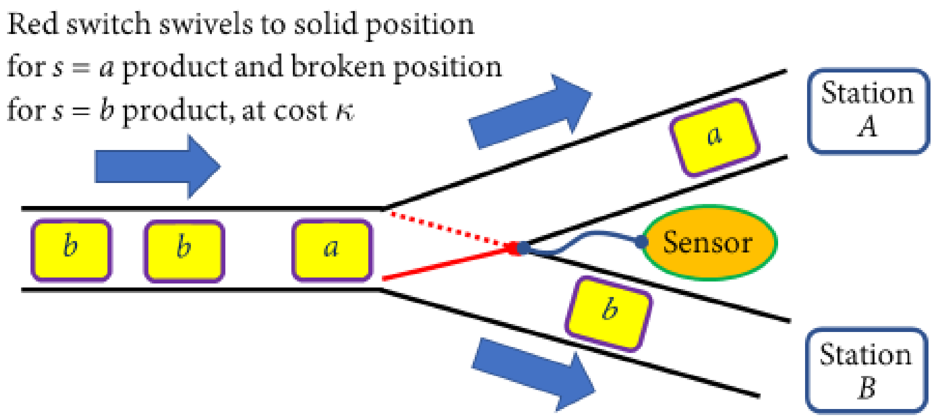

Figure 13. Using signals to differentiate produce but at a cost

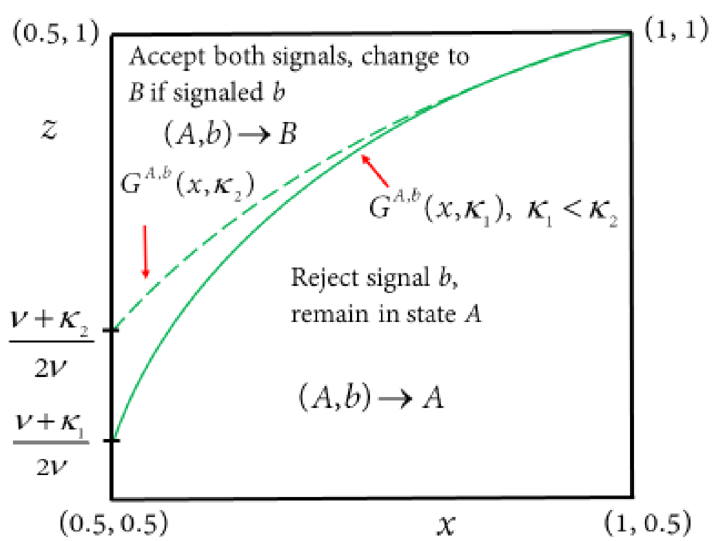

Figure 14. Inertial bounds under energy costs, case when in *A*

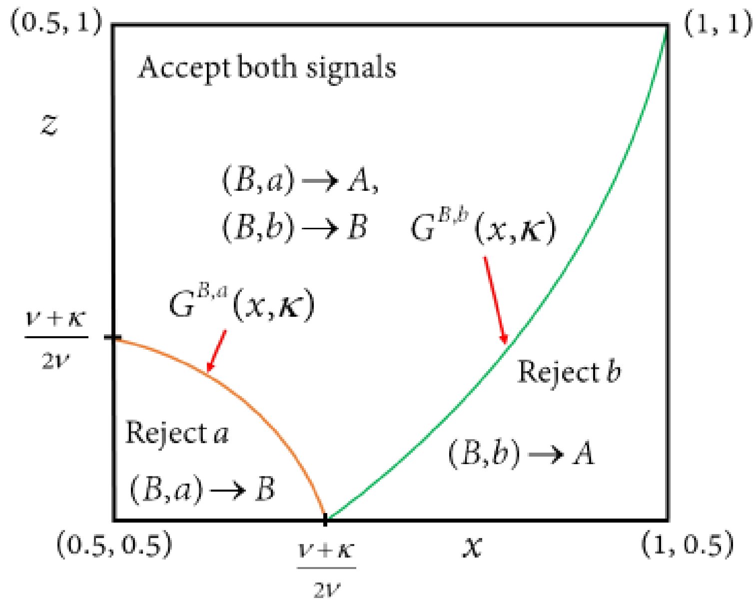

Figure 15. Inertial bounds under energy costs, case when in *B*

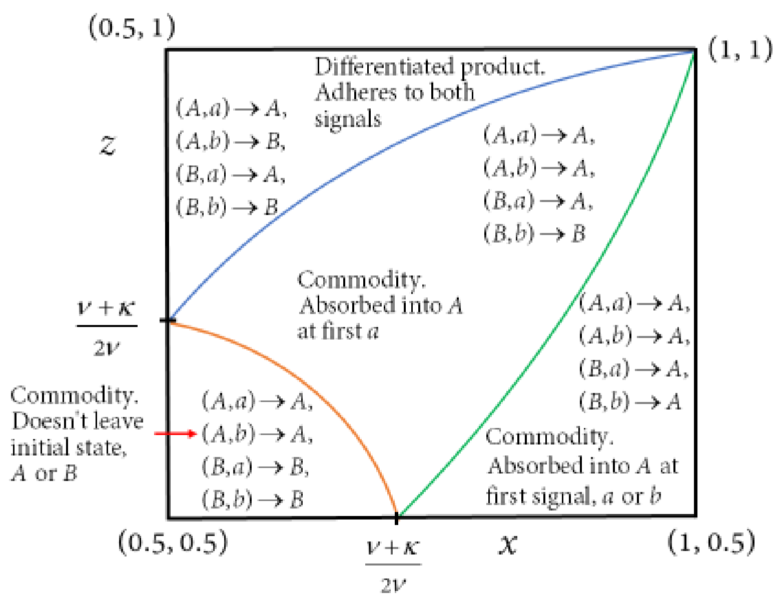

Figure 16. Signal-conditioned transition dynamics under Marshallian bounds