Supply & Demand For Automation in Production Agriculture

David A. Hennessy
ER Smith Professor of Agric. & Food Policy
Michigan State University

Friday, January 3, 2020

Agriculture's Resistance to Automation

- "To make machines operate efficiently, one feature of mechanized production is the uniformity of operation in a field. … 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." (Zhang 2018)
- In crop agriculture, transactions cost view of Allen & Lueck (2004). Seasonality & nature's randomness give the family farmer agency cost advantage over a more industrial approach that more than offset very large scale economies from mechanization
- Is the bulwark breaking down?

Sensors

Stationary infrared lab instruments qualify whole batches of grain based on a few small, representative samples. An onboard sensor from Textron Systems could analyze grain during harvesting and allow a higher-quality product to be sold separately. Courtesy of Case IH Advanced Farming Systems.

The unit is the first in a family of rugged, inexpensive spectrometers developed by Textron. It combines a near-IR sensor and optics into a compact solid-state unit able to withstand harsh industrial environments at a cost below $10,000. The sensor shines the light through a sapphire window on a grain flow and measures the reflected wavelengths. From this, an onboard computer calculates protein or moisture and oil content based on mathematical models customized for the grain of interest. Grain composition data are displayed and stored in real time on a unit in the combine's cab. Analysis of the onboard system's results have correlated well with those taken in laboratory tests.

Source: L. Sheppard
https://www.photonics.com/Articles/Infrared_Grain_Analyzer_Goes_with_the_Flow/a5253

Objectives

- This paper does two things
- Offers a Bayes risk function model of decision-making under imperfect, but symmetric, information. Model explains product differentiation and preferences over factors. Can be used to characterize farm input level choices in presence of sensor information
- Relate above analysis to two technological revolutions, biotech and IT tech (Gallardo & Sauer 2018; Zilberman 2019), that are fundamentally altering agricultural production, food processing, retail & consumption

Literature Review

- Literature on how automation-focused IT is affecting factor demand in the economy at large
- Traditional approach views automation as capital-augmenting, increasing marginal value of capital vs. labor so that competitive forces lead to replacing labor with augmented capital
- A shotgun approach: relates little about why automation has favoured skilled labor over unskilled
- Acemoglu & Restrepo (2018) take a more granular, realistic, perspective on factor use. They characterize a menu of tasks each of which can be completed by capital or labor but where the factors differ in comparative advantage

This Presentation's View

- We argue that capital's comparative advantage on tasks has been in exploiting what may be labeled as uniformity, standard settings and consistency, or *C*
- Labor's comparative advantage on tasks has been in discernment, or *D*, to accommodate inconsistencies, so a labor focus persisted in agricultural environments that did not yield to standardization
- But with advent of IT, and especially sensing technologies, that comparative advantage is eroding, first in factory and now on farm

Basic Symmetric Loss Model

- Two raw materials types, A and B, available for discernment (D), possible differentiation and subsequent transformation

- Point of discernment can be at harvest, a commodity intake point or during processing

- Capacity allocated to discernment can take
  - labor form, as in a worker charged with sorting, or
  - capital form, as in a sensor-enabled machine

Story: Pear Tomatoes

- Rasmussen 1968 and Webb & Bruce 1968. Redesigning Tomato for Mechanical Production
- California tomatoes for processing shifted from hand-picked to mechanically harvested during 1964-1970
- First came i) variety, then ii) harvester, then iii) adaptation to promote uniform production

Needed field conditions promoting consistent, uniform growth + easy harvest for all crop: field levelling, irrigation, transplanting

Prof. G. C. Hanna of University of California, developer of tomato variety VF 145. This is first and still most popular machine-harvestable tomato variety.

Story: Call it the Prior

Source: Fresno State University
http://www.fresnostate.edu/jcast/cati/update/2013-winter/sodic-soils.html

Think Allen & Lueck transactions cost theory
Looking for information rich prior in Bayes' sense

Story: Balancing Losses

- Harvester expensive to operate: 12 workers onboard to separate quality, ripe tomatoes from green/blemished fruit and dirt
- Two forms of loss. Grade
  - Leniently: materials harm product reputation or prove difficult to process
  - Harshly: lose good fruit
- By mid 1970s, loss calculations changed. Most workers replaced by accurate color-reading sensors linked with air-blaster to discard flagged tomatoes (Huffman 2012)

Commodity & Product Differentiation

- Investopedia writes that a **commodity** is
“a basic good used in commerce that is interchangeable with other commodities of the same type. … The quality of a given commodity may differ slightly, but it is essentially <u>uniform</u> across producers.”

- But quality difference isn’t enough; one must
  (benefits) care about difference, and
  (costs) be able to measure it cheaply

Main thesis of this work is that ability to detect differences cheaply is core determinant of both commodity form and how agricultural automation has evolved

Basic Model

Fraction $x \in [0.5,1]$ of raw materials is type A, rest type B. We refer to x as the C index. Raw materials become more consistent in type as x value increases from 0.5 to 1.

Two more parameters required to formalize model, one for info processing

When handling raw materials, capacity receives 1 of 2 signals about the materials, $s \in \{a,b\}$.
Lower case signals corresponding upper case true type

Basic Model, Cont'd

Capacity differs along one dimension, namely by the capacity unit's D index, z. If a capacity unit has discernment level z then fraction z of actual material type A signals as type A, i.e., $s = a$.

This is test sensitivity embedded in the resource

Probability signal is A given that type=A is

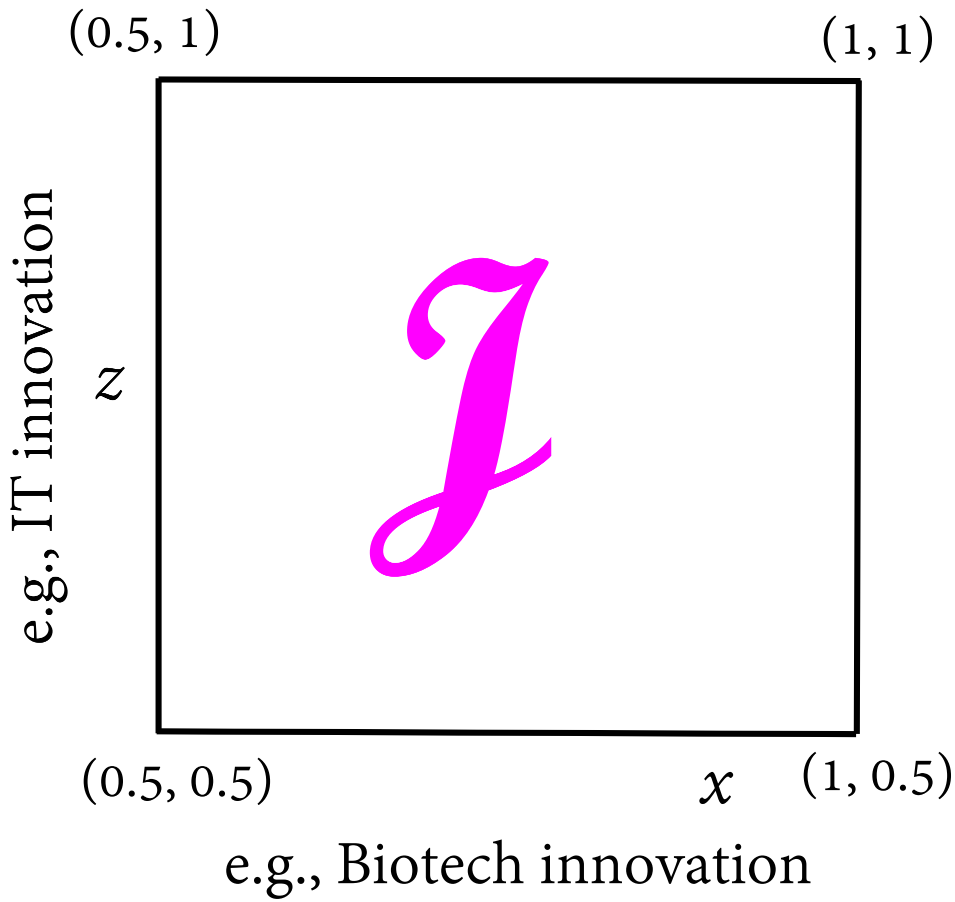
$P(a \mid A, z) = z$ where

$P(\cdot \mid I)$ = probability conditional on information I.

Restricting $z \in (0.5, 1]$ we also impose probability signal is B given type=B to be

$P(b \mid B, z) = z.$

Figure 1. C-D Space



Premise 1 (P1). Space of interest is this $\mathcal{J}$ box

Role of Incentives

Assume types have same value and calculate expected dollar loss from mis-classification; or assume a difference in value for types.

Let $\mathcal{L}(z,x)$ = expected loss from mis-classification

So seek low value for $\mathcal{L}(z,x)$.

Premise 2 (P2). Raw material owner seeks to minimize over (x,z) expected loss from mis-classification, $\mathcal{L}(z,x)$.

Role of Incentives, Cont'd

Premise 3A (P3A). Prices for types are common. Loss from assuming Type B when really Type A **equals** that from assuming Type A when really Type B.

For blue, lose nothing

For red, lose v in each case

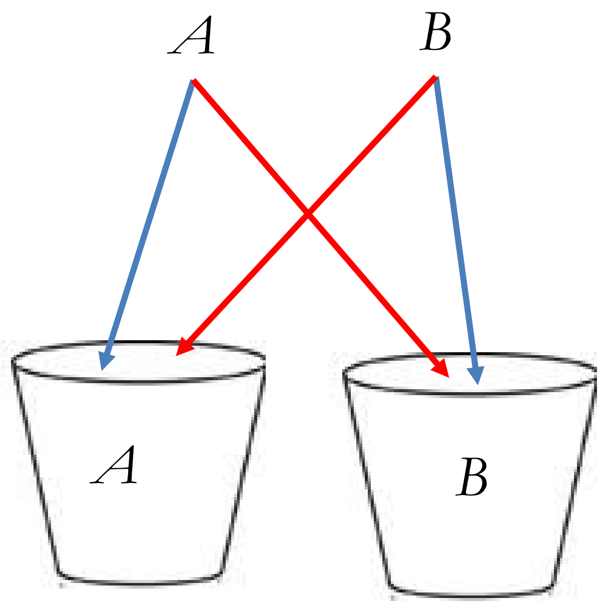


Figure 2. Representing Signals & Losses

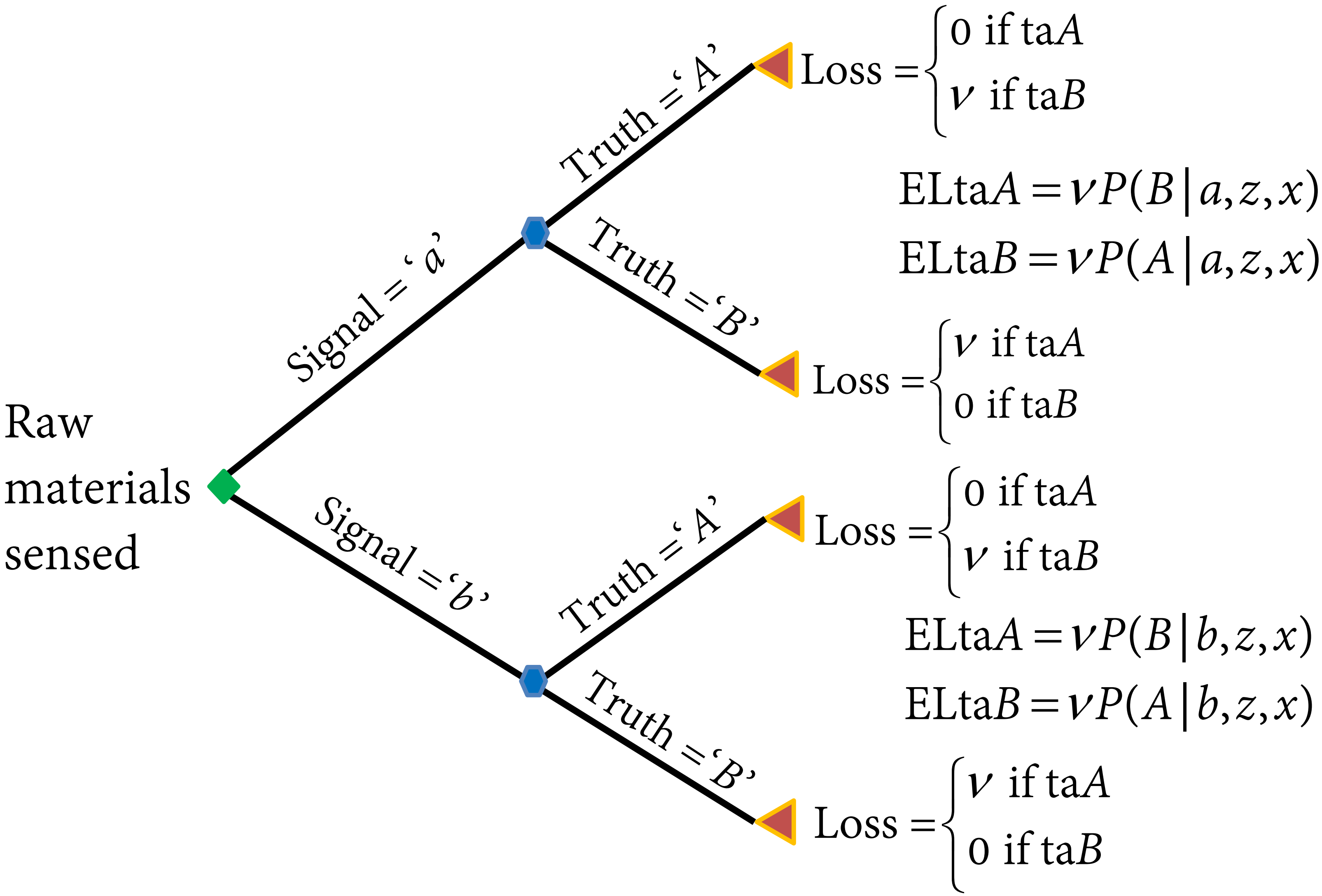
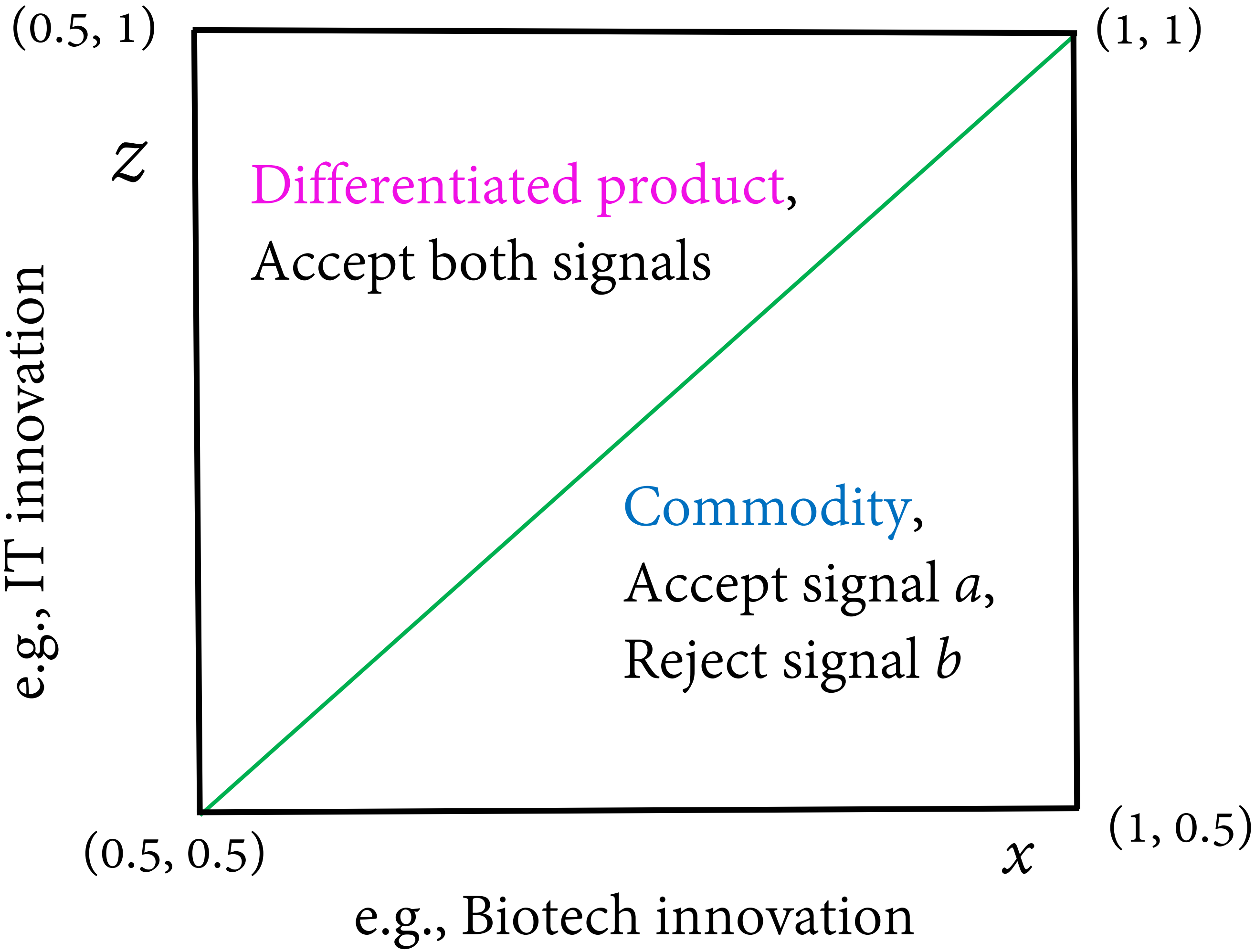


Figure 1 (again). Product Differentiation



Information Input Costs (Draft)

Materials with consistency x costs $r(x;\theta)$.
Parameter θ indexes the state of C technology.

Materials with discernment z costs $w(z;\lambda)$.
Parameter λ indexes the state of D technology.

Total cost is

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

Staple Discernment to Which Factor?

Could have D potentially attached (stapled) at a factor cost to either factor in the following manner:

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

$e(z)$ increasing & convex. The ratios are productivity indices attached to respective factors

C-D Shifters

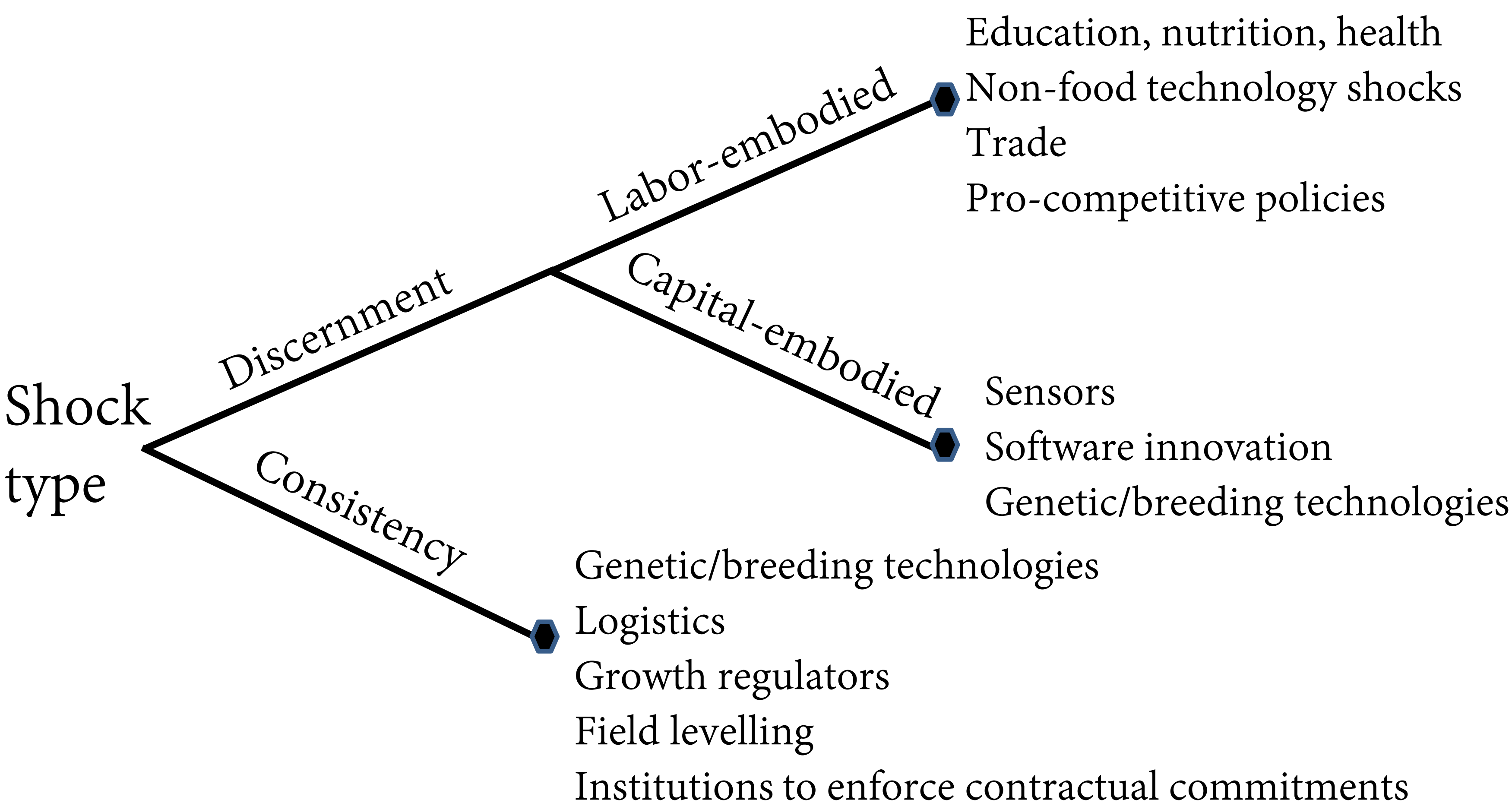


Figure 5. Schema for Shocks to Marginal Costs of *C* & *D*, as Inputs into Food Production/Processing

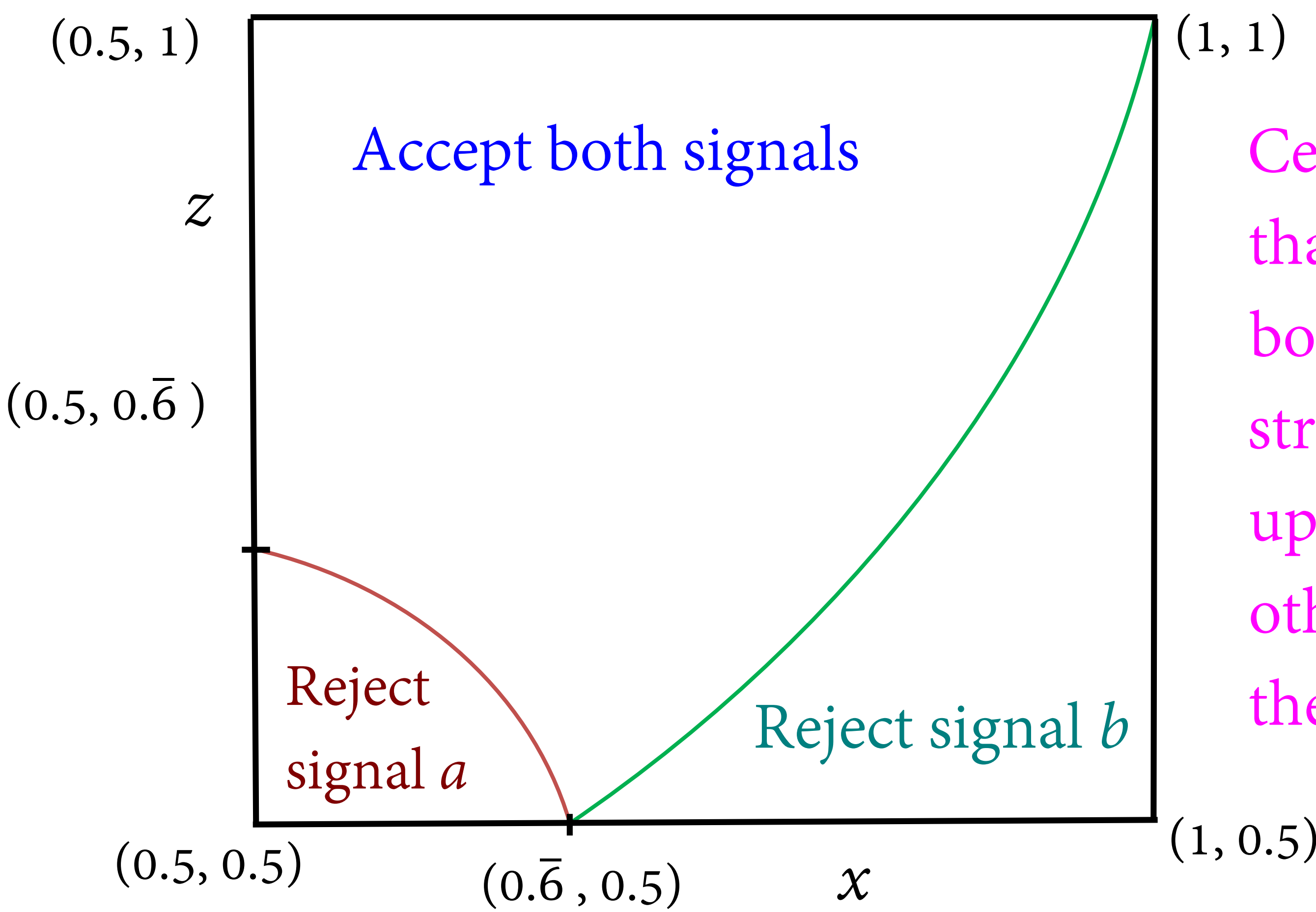
Loss Asymmetry

Here we relax P3A to consider when magnitude of loss from mis-categorizing differs by form of mis-categorization. Green tomatoes may adversely affect value of processed tomatoes by more than losing a perfect processing tomato. Or reverse may be true

Premise 3B. Loss from assuming Type B when material is Type A equals $\nu_A > 0$. Loss from assuming Type A when material is Type B equals $\nu_B > 0$ where $\nu_A \leq \nu_B$.

For analytic convenience we specify $\tau = \nu_A / \nu_B > 0$. Whenever $\tau > 1$ then the cost of mis-categorizing Type A as Type B exceeds that of the converse error.

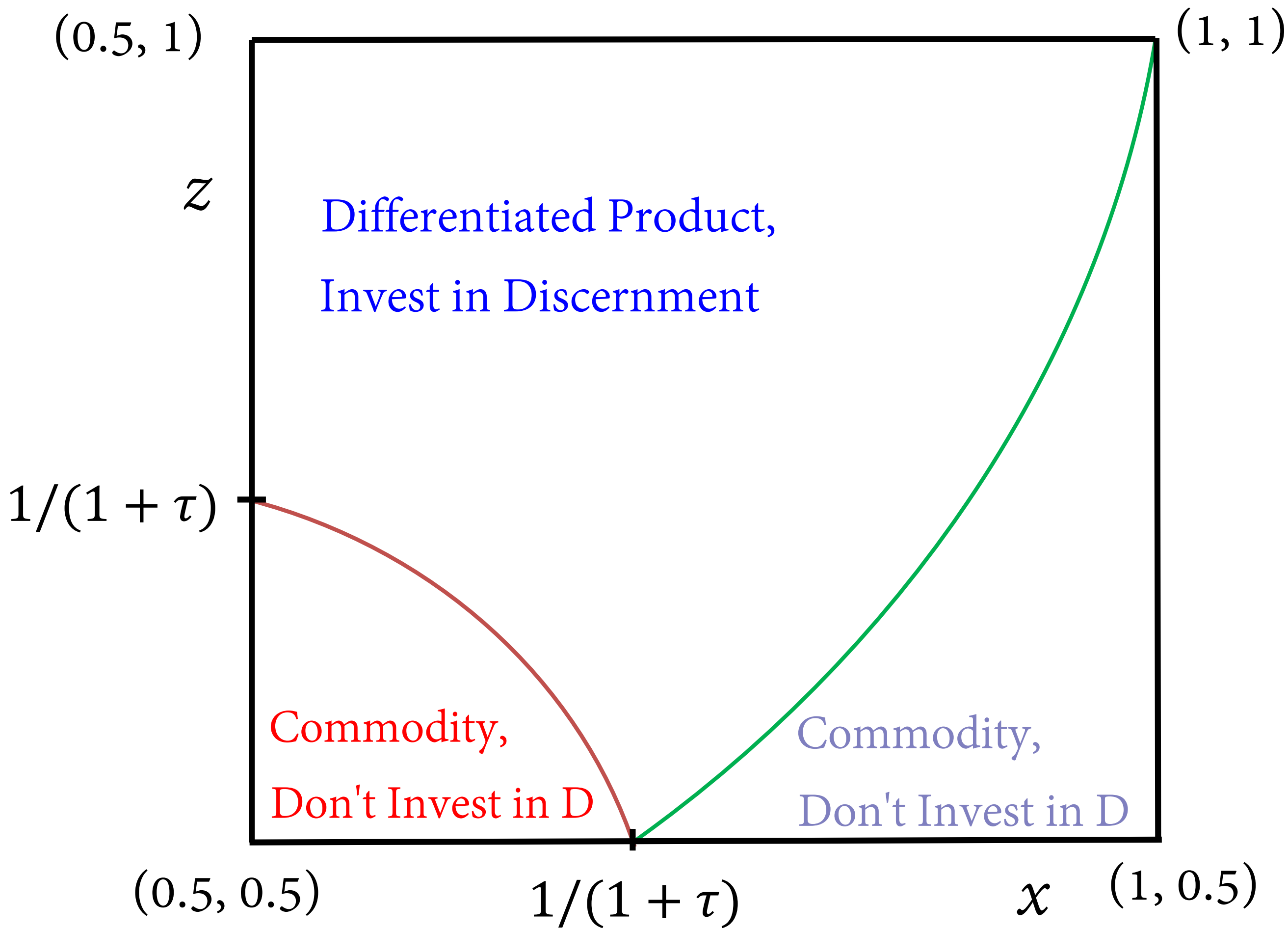
Signal Accept, Reject Regions



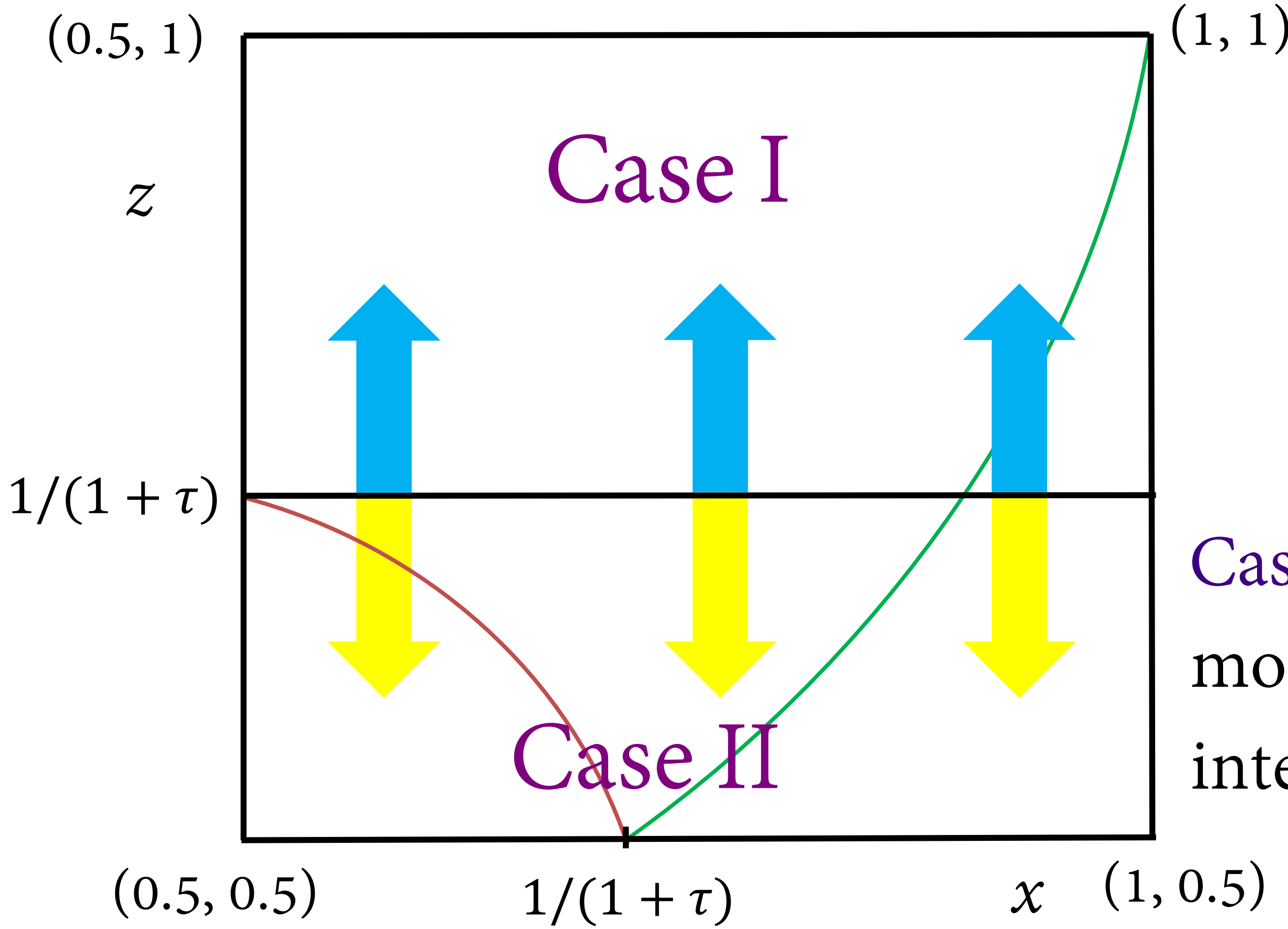
Central point is that there are two boundaries. One stretches half way up z axis. The other going all the way

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

Product Differentiation



Two Cases



Case II
more
interesting

Discernment Marginal Loss

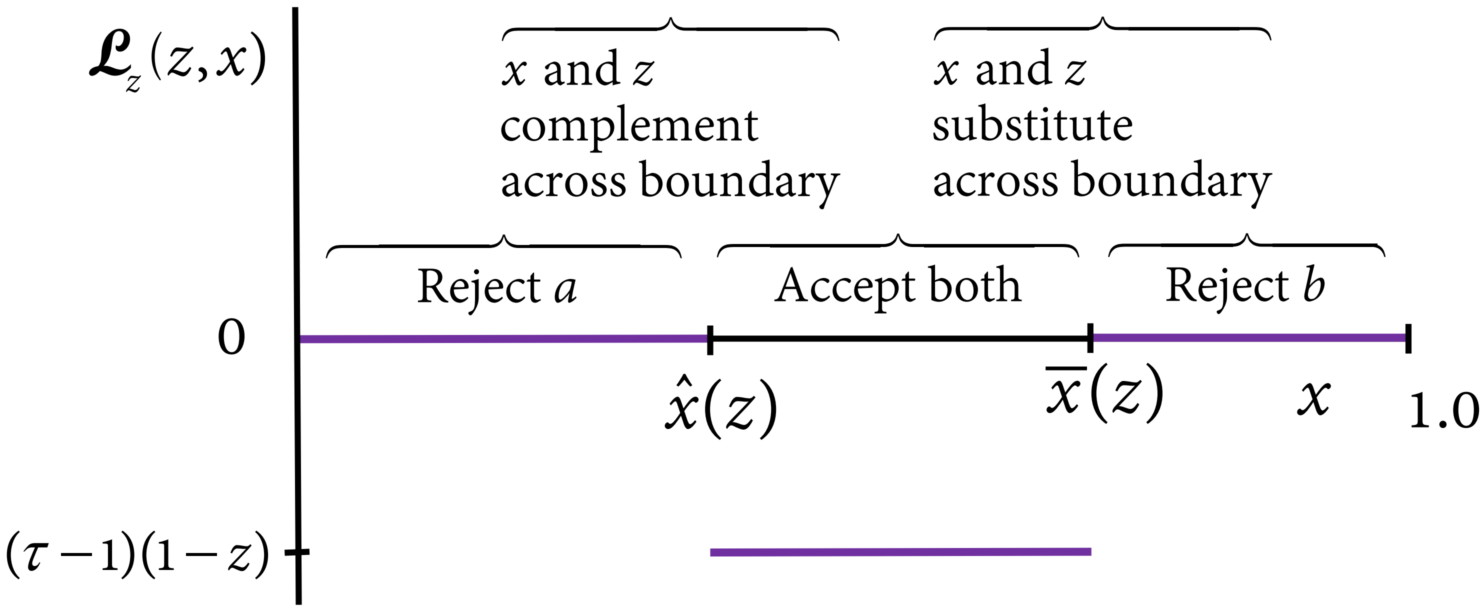
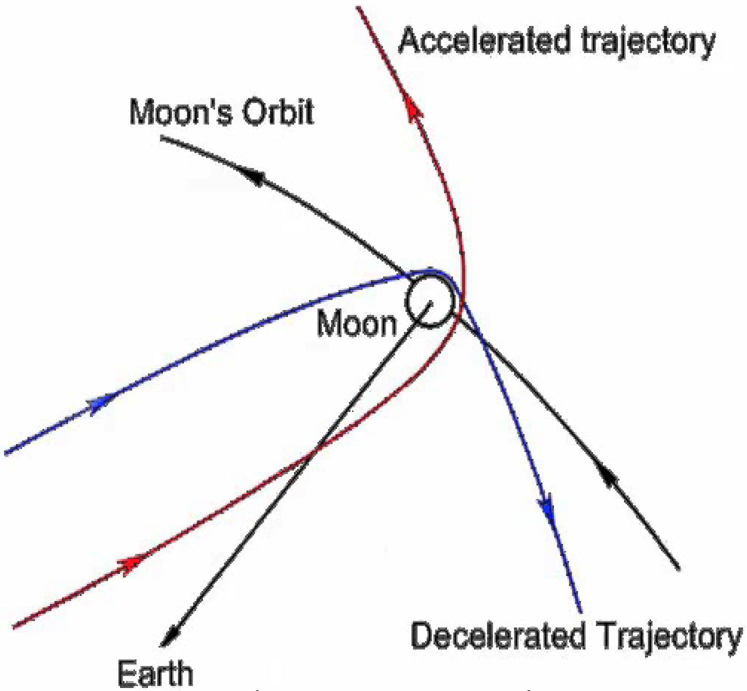


Figure 11. Case II UEL marginal response to discernment at different consistency levels

Slingshot Effect, (Apollo 13) see

https://www.youtube.com/watch?v=3Jb-titkmbU

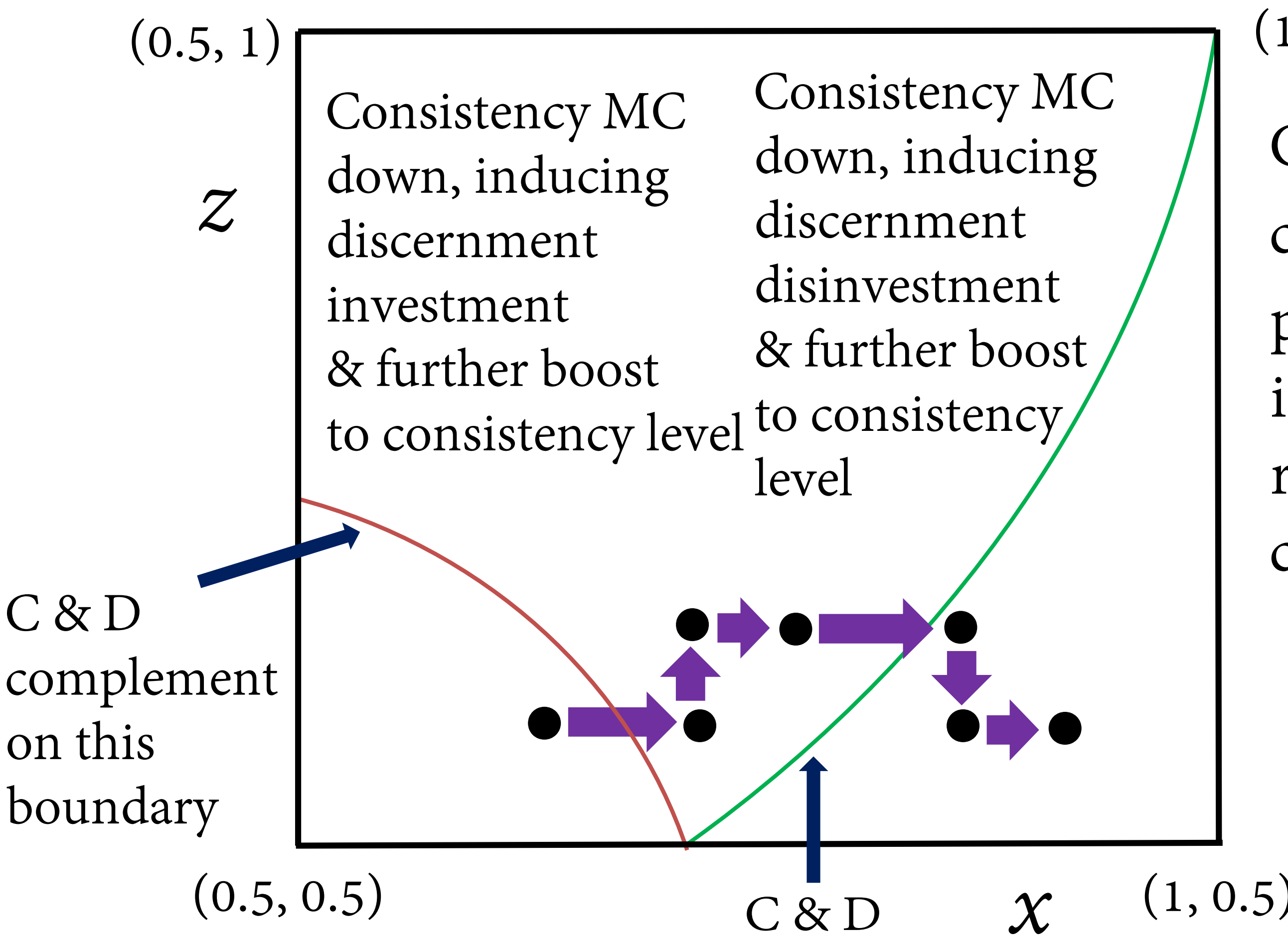


The slingshot effect can result in either an increase or a decrease in a space craft's velocity, of varying amounts, depending on it's direction of approach and departure from the planet or other body.

Object accelerates if entering a body's gravity field, moon here, in same direction as body's orbit.

Gravity draws in and then centrifugal force slings out

C is Object, D is Orbiting Moon



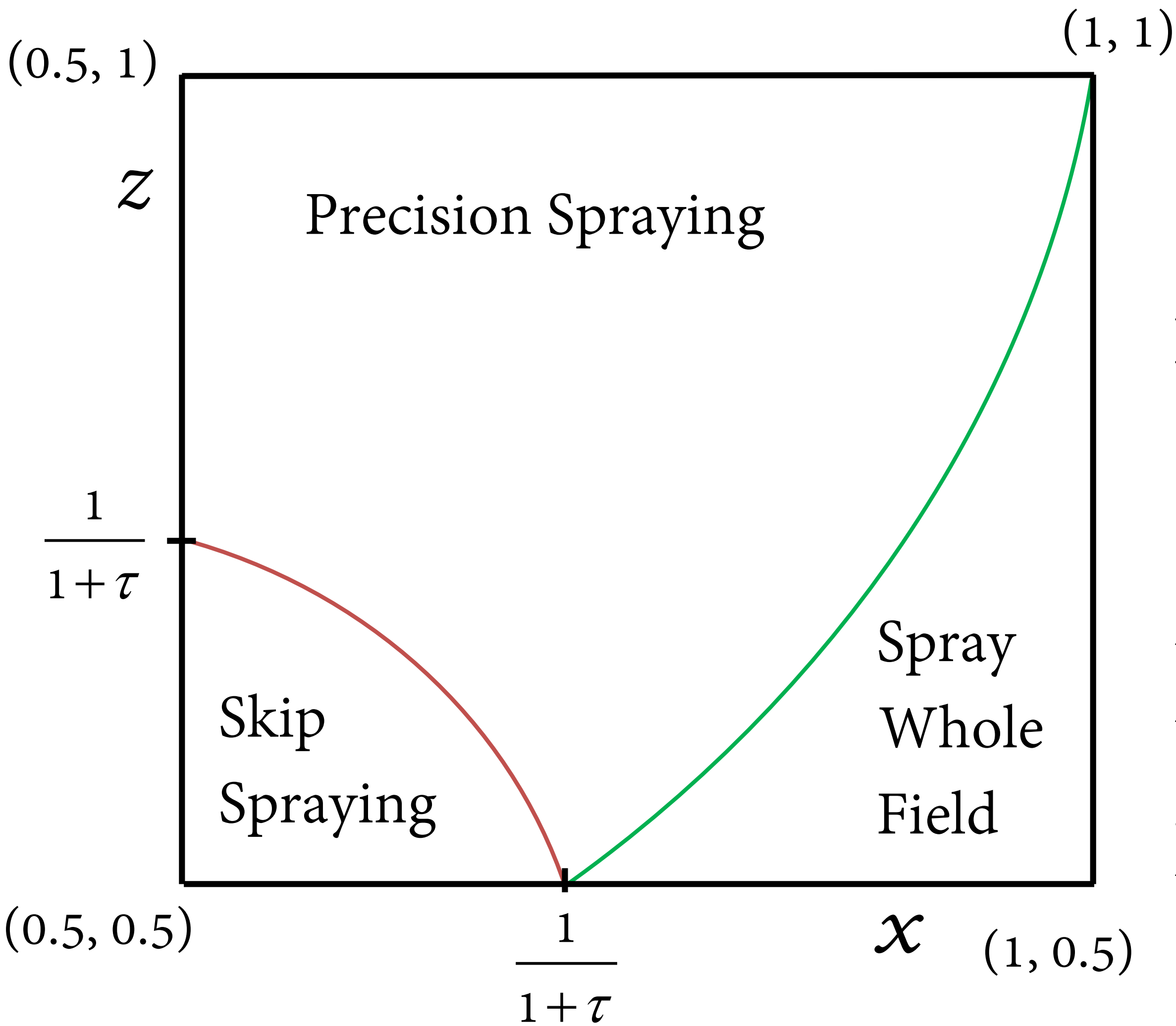
Given low consistency, let plant science innovations reduce *C* marginal cost through θ up

Discernment assist coming into and going out of differentiated product region

Another view:

D catalyzes more *C*

Weeds



Precision ag. economics literature has applied Bayesian analysis (Babcock et al. 1996), but not for decision analysis in the temporal way that precision machines need to take them

REFERENCES

- Acemoglu, D., & P. Restrepo. 2018. Modeling Automation. American Economic Review 108(May):48-53
- Allen, DW, & D Lueck. 2004. The Nature of the Farm: Contracts, Risk and Organization in Agriculture (MIT Press, Cambridge MA)
- Gallardo, RK, & D Zilberman. 2016. The Economic Feasibility of Adopting Mechanical Harvesters by the Highbush Blueberry Industry. HortTechnology 26(3):299-308
- National Acad. Sciences, Engineering, & Medicine. 2019. *Science Breakthroughs to Advance Food and Agricultural Research by 2030*. Washington, DC: The National Academies Press.
- Rasmussen, WD. 1968. Advances in American Agriculture: The Mechanical Tomato Harvester as a Case Study. Technology & Culture 9(4, October):531-543
- Schmitz, A, & D Seckler. 1970. Mechanized Agriculture and Social Welfare: The Case of the Tomato Harvester. AJAE 52(4):569-577
- Webb, RE, & WM Bruce. 1968. Redesigning the Tomato for Mechanized Production. Yearbook of Agriculture, 1968: Science for Better Living, U.S Dept. of Agric., Washington DC., 103-107
- Zhang, Q. 2018. Tree Fruit Production Automation. In Zhang, Q. (ed.), Automation in Tree Fruit Production: Principles and Practice, 1-12 (CAB Inter', Wallingford, UK)
- Zilberman, D. 2019. Agricultural Economics as a Poster Child of Applied Economics: Big Data & Big Issues. AJAE 101(2, March):353-364