How will regulation influence commercial viability of autonomous equipment in US production agriculture?

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Abstract – Autonomous equipment for crop production is on the brink of commercialization in the United States but federal, state, and local policies could affect commercial viability and hinder adoption. This study examines the farm-level implications of both a speed restriction and on-site supervisory regulations. The rules reduce the profitability of autonomous machinery and for some scenarios autonomous machines are no longer an economically viable alternative to conventional machinery. Regulations also increase the optimal number autonomous machines required and influence production practices. Smaller farms have more flexibility in supporting the rules because they have more to gain from use of autonomous equipment.

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Introduction

Autonomous equipment in production agriculture is on the verge of commercialization in the United States and worldwide. From large machinery manufacturers to small non-traditional manufacturers and startups, there is a race to make autonomous equipment in U.S. production agriculture technically and economically feasible. Goldman Sachs predicts that the small autonomous tractor market will be a $45 billion industry (Daniels 2016). While autonomous equipment in agriculture has been the subject of research efforts for decades, mainstream media has only begun reporting on the opportunities that autonomous equipment offers to the agriculture industry. Those reports highlight that autonomous equipment can help feed the world and solve the labor shortage in agriculture (Kolodny and Grigham 2018). In the United States, labor shortages in agriculture has increased since 2018, with new immigration policies and the realization that pandemics, such as COVID-19, can exacerbate these issues. Skilled labor shortages in the agriculture sector are not just an issue in the U.S. but globally and are a critical constraint facing agriculture, especially for essential operations requiring timely completion. Other media outlets highlight that autonomous equipment will "revolutionize" fieldwork in agriculture and introduce prototypes that are ready for commercialization, like Smart Ag's autonomous grain cart and Seedmaster DOT's autonomous platform, both now acquired by Raven Industries (Mark 2018; Belz 2018).

The replacement of large, manned farm machinery with smaller, autonomous machinery has numerous benefits without losing the benefits traditionally afforded to larger machinery (e.g., economies of size, timeliness of operations, and capital-labor substitution). While removing the operator from the cab has direct labor and opportunity cost implications, especially those farms operating multiple sets of equipment (e.g. two planters), additional benefits exist. First, there is potential to lower the capital cost of equipment in production agriculture (Lowenberg-DeBoer et al., 2021). Second, the adoption of small autonomous machinery will offseting the environmental consequences of larger farm machinery. As the size of farm machinery increases, soil compaction is more prevalent, which results in lower yields. Additionally, it is becoming more challenging to apply a uniform application of inputs as machinery increases, resulting in off-target application and higher input costs. Furthermore, if a large conventional machine goes down with problems, there is typically not a second waiting to continue operations. With smaller, autonomous machinery operating in fleets, if one does go do, the other machines can continue operations. While autonomous machinery does not have to be smaller, the benefits listed above explain why some manufactures are developing automonous prototypes smaller than conventional machinery. Even though autonomous machinery is near commercialization, federal, state, and local policies could impede adoption and economic feasibility (Luck et al., 2011; Redhead et al., 2015; King 2017; Shockley, Dillon, and Shearer, 2019; Trimble, 2019).

Currently, there are no federal policies on autonomous farm equipment in the United States. However, a precedent has been set at the state level by the current restrictions for California's autonomous equipment. According to the current California code, the operator must monitor and supervise the tractor and surrounding workers at all times, and the autonomous equipment cannot exceed two miles per hour. For comparison, typical corn planting speed is four to six miles per hour and applying pesticides with a self-propelled sprayer is ten to fifteen miles per hour depending on field conditions and characteristics. A human supervisor, not located on the premise, would not adhere to the current California code. The current California code is dated and protects worker safety under the technology available at the time (Raven 2001). Since the policy's enactment, sensor technology, intelligent controls, safety measures, advanced guidance systems, and artificial intelligence have rapidly advanced. If other states or the federal government, without substantial change, adopts California's current restrictions on autonomous equipment, this could hinder the commercialization and innovation of autonomous equipment in agriculture for the United States (Janzen 2017)

While autonomous equipment for crop production is on the brink of commercialization in the United States, federal, state, and local policy uncertainty will impact the economic viability and hence, adoption. Two missing elements in previous economic studies are on-site supervisory requirements and speed restrictions that California's policy impose. Therefore, this study aims to expand upon Shockley, Dillon, and Shearer (2019) to assess the farm-level implications of California's policy on the economic feasibility of operating autonomous equipment in U.S. grain production. The specific objectives include:

1) Determine the economic impact of a supervisor monitoring each autonomous machine while operating versus one supervisor monitoring the entire fleet of autonomous machines while operating;
2) Determine the impact a speed restriction has on economic viability and the number of autonomous machines required for grain crop production;
3) Determine the economic impact of a policy mandating both an on-site supervisor and speed restriction; and
4) Determine if a supervisor requirement and speed restriction influence the economic feasibility of autonomous machinery for various farm sizes.

This study provides insights into the on-farm economic consequences of mandatory on-site monitoring of autonomous equipment and speed restriction for grain operations in the U.S. Policymakers interested in federal, state, or local restrictions on autonomous machinery should consider the results of this study before enacting policies that could hinder the economic viability of autonomous machinery in grain crop production.

Economic and Policy Review of Autonomous Machinery in Agriculture

Macroeconomic and microeconomic questions still exist with the commercialization of autonomous equipment in production agriculture. How will autonomous equipment impact labor markets? Are modifications needed to the structure of current insurance programs? Will policies at the federal, state, and local levels restrict ownership and provide operational guidelines? What is the farm-level profitability of autonomous equipment?

Most studies focus on farm level profitability with the goal of informing engineers in the research and development of commercial prototypes (Goense 2005; Pedersen et al. 2006; Pedersen, Fountas, and Blackmore 2007; Shockley, Dillon, and Shearer 2019). Lowenberg-DeBoer et al. (2019) conducted a systematic review of published autonomous equipment studies from 1990-2018. They found 18 contained some form of economic analysis, mostly partial budgets, and all identified scenarios in which autonomous equipment in agriculture would be profitable. Shockley, Dillon, and Shearer (2019) conducted a whole farm planning analysis that compared autonomous equipment to conventional grain production in the United States. This study identified the economic feasibility and break-even levels of investment for intelligent controls to guide research and development. Furthermone, this study illustrated that autonomous equipment provides the opportunity for smaller operations to realize economies of size typically only achieved by larger farming operations. However, the suite of benefits will depend on the type of autonomous equipment that becomes commercially available.

Lowenberg-DeBoer et al. (2021) expanded the economic literature by examining autonomous equipment's economic feasibly in field crops in the United Kingdom. Shockley, Dillon, and Shearer (2019) and Lowenberg-DeBoer et al. (2021) employ linear programming to demonstrate how autonomous equipment shifts the production costs curves for various farm sizes and structures. Lowenberg-DeBoer et al. (2021) utilized data collected from the Hands Free Hectare project at Harper Adams University. They actively experiment with and operate autonomous equipment at scale by retrofitting a conventional tractor with autonomous technology for grain crop production. While economic feasibility studies exist, no studies examine the implications of various policy restrictions on field operations.

Policy Review of Autonomous Machinery in Agriculture

At the federal level, no policies currently exist for regulating autonomous machinery operations in agriculture across the U.S. However, California's autonomous farm equipment operations are governed by the Occupational Safety and Health Administration (OSHA, California Code of Regulations, Title 2, Section 3441 (b)). This code requires that an operator be present at the vehicle's controls, but not necessarily in the tractor's cab, potentially with remote access. However, for remote operations, the controls must be readily accessible. Futhermore, autonomous machinery must not exceed two miles per hour when in operation.

Federal regulations do exist for other autonomous aerial technologies for agriculture. The Federal Aviation Administration (FAA) regulates unmanned aerial systems (UAS), a.k.a. unmanned aerial vehicles and drones, operating in production agriculture. If UASs collect data on the farm for making management decisions, their classification is for Commercial Use. Under this classification, the owner must follow the FAA's Part 107 regulations. These included becoming a certified UAS pilot, registration and appropriate display of assigned number on the UAS, and adherence to the FAA rules of operation. These federal rules of operation include limiting UAS size, operational speeds, and time of day of flying. Furthermore, the rules require mandatory oversite and have restrictions on operating in certain weather conditions and cargo (Murphy and Bergman 2020; United States, Federal Aviation Administration 2019). Various states also have policies for UAS operations. In 2019, six states prohibited flying UASs over correctional, defense, and telecommunications facilities, as well as railroads (National Conference of State Legislatures 2020b).

The United States is not alone regarding the lack of policies for operating autonomous equipment in production agriculture. Currently, the E.U. Machinery Directive 2006/42/EC guides all agriculture equipment operating in the European Union. These guidelines include road and operator safety, as well as environmental standards. However, members of the European Union have different rules for operating tractors on farms and roadways. Germany currently has operational guidelines for highly automated tractors that includes safety measures like shut down requirements and speed restrictions. On the other hand, the United Kingdom has the opportunity to define and develop new policies regarding autonomous farm machinery operations since their recent departure from the E.U. (Lowenberg-DeBoer et al. forthcoming; European Commission 2010). In Australia, there are limited regulations for operating autonomous equipment on private property. Therefore, Australian agriculture lobbying groups and manufacturer associations are taking the initiative to develop operating policies and procedures in hopes of adoption at the state and federal levels (Grain Producers Australia 2019).

Economic Model

Consistent with the study objectives of evaluating the farm-level economic impacts of potential autonomous machinery policies, the research methods employed in this study consist of a mathematical programming framework similar to Shockley, Dillon, and Shearer (2019). This multi-faceted whole farm planning model is a mixed integer formulation and incorporates three optimization models: resource allocation, machinery selection, and sequencing. The model evaluates how cropping practices, machinery management, labor requirements, and timing of field operations change with the introduction of autonomous machinery for a Western Kentucky commercial corn and soybean producer. With updating Shockley, Dillon, and Shearer (2019), prescriptive solutions to the policy issues the autonomous machinery industry faces can be evaluated. The remainder of this section will provide a general model description followed by a more detailed discussion of the model enhancements, experimental policy procedures, and data updates germane to this study.

Model Description

In the tradition of neoclassical microeconomic firm theory, the objective function presented in Shockley, Dillon, and Shearer (2019) reflects a farm manager's desire to maximize net returns above specified costs. These specified costs include input costs associated with the optimal enterprise mix and production levels. Additional costs include the variable and fixed costs associated with the optimal machinery choice. Therefore, the estimated net returns represent a return to land, management, overhead labor, and other overhead expenses. The decision variables incorporated in the mathematical programming model include production, marketing, and machinery management decisions. Production decision variables reflect the land planted in corn and soybeans as defined by planting dates and maturity groups relevant to the study area.

Corn and soybean sales accounting variables reflect the marketing component of the model. The machinery decision variables are the foundation of the whole farm planning model and provide insight into the optimal size of conventional machinery and the optimal number of autonomous vehicles (and implements) required to perform specific agricultural field operations common in grain crop production. Like Shockley, Dillon, and Shearer (2019), the application of lime, phosphorus, and potassium are custom-hired activities. Furthermore, harvesting activities are custom hired. An accounting variable for the accumulation of required machinery supervisory time is also included in the model.

Constraints represented in the formulation include a series of accounting equations for net returns calculation, crop marketing balances, and computation of required supervisory time. Resource constraints include land and machinery operation time due to suitable field conditions for all associated activities. Furthermore, sequencing constraints assure proper timing of machinery operations and the implementation of a two-year crop rotation.

Model Enhancements and Experimentation Procedures

The expansions of the mathematical programming model described above from Shockley, Dillon, and Shearer (2019) primarily relates to modeling a new autonomous machine prototype (described the data section below), implementing the speed limit restriction, and modeling the supervision policies. Internal calculations of autonomous performance rates (acres operated per hour) allow for analyzing a speed limit restriction of two miles per hour with ease. However, to reflect the new autonomous machine prototype and analyze supervisory restrictions, adjustments to the base model are required. Specifically, the base case assumes an on-site supervisory time of autonomous machines equal to 10% of total machinery time, consistent with Lowenberg-DeBoer et al. (2021). This labor cost also includes the replenishement of seed, fertilizer and pesticides for field operations. The following balance equation reflects the inclusion of a base supervisory time:

$$\sum_{c,cpd,mo,wk} PerfRate_{c,mo} OPER_{c,cpd,mo,wk} - \frac{1}{Supervise\ \%} SUPVSETIME * BUYTRACT = 0$$

Where the sets include crops (c), crop planting date (cpd), machinery operation (mo), and week (wk); coefficients include performance rate (PerfRate, in hr/ac) and supervision percentage time (Supervise %, specifically 10% for the base case). The inclusion of supervision percentage time allows for analyzing any policy restriction addressing a fleet of autonomous machines' mandatory supervision. The variables include decision variables for the performance of machinery operations (OPER in acres), an accounting variable for supervision time (SUPVSETIME in hours annually) and an integer decision variable for the purchase of tractors (BUYTRACT). For a per machine on-stite supervision regulation case, the integer purchase decision variable (BUYTRACT) in the above equation is omitted. Given the nonlinear term and integer variable inclusion, the model is now a mixed integer nonlinear programming model. TO allow on-site supervision of the fleet by a single human, it is assumed that all autonomous machines are working in one field.

Data: Programming Model Coefficients

Data needed for the model may be categorized as economic (objective function coefficients), technical (coefficients), and resource endowments (right-hand side values). Economic data consists of expected crop prices and specified costs for production and machinery operation and ownership. Expected prices for corn and soybean are \$3.71/bu and \$9.03/bu, respectively. These crop prices reflect the three-year marketing average prices for Kentucky, less \$0.17/bu hauling cost (USDA-NASS 2020a; Halich 2020a). Specified costs include operating and ownership costs for the conventional machinery options outlined in Table 1 and 2020 custom hire rates applicable to Kentucky (Halich 2020a; Laughlin and Spurlock 2020). While lime, phosphorus, and potassium applications are assumed custom hired, the application of nitrogen fertilizer is conducted by conventional or autonomous machinery. All conventional machinery specifications are from the Mississippi State Budget Generator, which follows the American Society of Agricultural and Biological Engineering (ASABE) Standards D.497.7 and EP496.3 (Laughlin and Spurlock 2020). The input rates and associated costs for planting, spraying, and fertilizing applications are from the 2020 Kentucky no-till grain crop budgets (Halich 2020b).

In addition to conventional machinery, autonomous machinery data are required to evaluate policy impacts of economic viability. The current status of autonomous equipment ranges from small, one row, machines that perform specific taks (e.g., "Xaver" by Fendt (AGCO) and Naio Technologies' weeding robot) to medium and large autonomus tractors capable of multiple tasks via implement attachments (e.g., DOT's autonomous platform, John Deere's autonomous electric tractor, CNH Industrial and New Holland autonomous tractors). While there are numersous examples of machines developed for autonomous operation, another pathway for autonomous equipment in U.S. production agriculture is retrofitting autonomous technology on current conventional tractors (e.g., Raven's OmniDrive system, X-Pert by Precision Makers, and Autonomous Solutions). In addition to the economic study by Shockley, Dillon, and Shearer (2019) that examined a medium sized autonomous tractor, Lowenberg-DeBoer et al. (2021) recently evaluated the economic feasibility of retrofitting autonomous technology on current conventional tractors in the United Kingdom via the Hands Free Hectare (HFH) demonstration project. Similar to Shockley, Dillon, and Shearer (2019), Lowenberg-

DeBoer et al. (2021) found that retrofitting autonomous technology on current conventional tractors is technically and economically feasible.

The data used herein reflects the retrofitting approach used by Lowenberg-DeBoer et al. (2021) as part of HFH project at Harper Adams University (Table 2). The HFH autonomous tractor a conventional 38 hp tractor ($19,500) that is retrofitted with hardware and software to enable autonomous operation. The hardware and software required for autonomous operation include safety equipment ($4,446), control systems and adaptations ($5,812), communications equipment ($1,110), and wiring ($780). Agro Business Consultants (2018) provided the initial investment costs for the autonomous tractor and are converted from pounds to dollars using an average September 2020 conversion ratio of 1GBP = $1.30USD (Board of Governors of the Federal Reserve System 2020).

Furthermore, the purchase prices for both the sprayer and nitrogen applicator implements used for autonomous operations are those estimated as part of the HFH project. However, the HFH project's planter was a grain drill and not representative of equipment used for planting corn and soybeans in U.S. production agriculture. Therefore, this study uses the same 4-row no-till planter in Shockley, Dillon, and Shearer (2019). All operating costs for autonomous field operations follow Redman (2018), while the autonomous performance rates and engineering parameters in Table 2 are determined using Witney (1995) and Laughlin and Spurlock (2020). While the autonomous tractor used for the HFH project is for small grain production in the United Kingdom, the retrofitting technology is readily available and transferable to conventional tractors in the United States.

Additional technical coefficients needed for model completion are expected crop yields by production practice and autonomous machinery benefits assumptions. Expected crop yields use the biophysical simulation data described in Shockley, Dillon, and Shearer (2019). Autonomous machinery use offers the potential for yield benefits due to the reduced compaction from smaller machines (McPhee et al., 2020;Asseng and Asche, 2019). While yield benefits from reduced compaction will vary across fields and operations, Murdock and James (2008) report a 7% yield reduction in corn and soybeans due to compaction in Kentucky. Therefore, a 7% yield increase is assumed as a autonomous machinery benefit. In addition to yield benefits, cost benfits exist for autonomus machinery from more targeted application of inputs (pesticides) using advanced machine vision (Relf-Eckstein, Ballantyne, and Phillips, 2019; Ruckelshausen et al., 2009; van Henten et al., 2009; Pederson et al. 2006; Blackmore et al., 2004). While the benefit from reduced inputs range from 12 to 90 percent in the studies above, a 10% reduction of select inputs, consistent with Shockley, Dillon, and Shearer (2019), is assumed for this study. All four benefit possibilities are examined for each policy case investigated.

A land resource endowment of 2,100 acres for the base case analysis reflects a commercial-sized farm in Kentucky. However, it important to examine farms of all sizes due to the impact automous machinery has on economies of scale. Given the average farm size in the U.S. is 444 acres, it is important to understand how autonomus machinery impacts smaller farming operations (USDA-NASS, 2020b). Therefore, land resource allotments of 500 acres and 3,100 acres are examined to address objective four of this study. The weekly total available time for performing machinery operations depends on expected suitable field days per week (Shockley and Mark, 2017) and the hours worked per day. The human operator limits conventional farm machinery to 13 hours per day (Shockley, Dillon, and Stombaugh 2011). However, autonomous machinery can operate 22 hours per day, allowing two hours for repairs and maintenance (Lowenberg-DeBoer 2019a).

Results

Given the model described above, autonomous machinery's economic viability without any policy restrictions is first determined. Table 3 outlines the unrestricted economic results for conventional and autonomous machinery based on each anticipated benefit scenario. The optimal conventional machinery set for the 2,100-acre corn and soybean farm is a 130 hp tractor, 8-row planter, 8-row fertilizer applicator, and a 60-foot sprayer, which results in an expected net return of $691,278. For all scenarios examined, autonomous machinery is an economically viable alternative to conventional machinery. Under the scenario of a yield increase coupled with a cost reduction, autonomous machinery increases expected net returns by 20.8% compared to conventional machinery. In all unrestricted autonomous farm scenarios, the optimal machinery management plan is to purchase two autonomous tractors.

When a supervisory regulation exists, either for each machine or for the entire fleet, autonomous machinery's economic viability decreases (Table 4). As anticipated, regulations requiring individual machinery supervision decreases net returns more than a fleet supervision regulation. An individual machine supervisory policy reduces autonomous machinery's profitability potential by 2.1% for the yield increase and cost reduction scenario. Not only does a supervisory policy influence the profitability of autonomous machinery, but it also affects the optimal number of autonomous machines. For a fleet supervisory policy, the optimal number of autonomous machines increases from two to three. This increase is explained in part by the lower marginal input cost of a machine under fleet supervision as compared to individual machinery supervision. While additional ownership and other operating costs for an autonomous machine are equal between the two scenarios, the marginal cost of supervisory time is zero for any additional autonomous machines required greater than one in the fleet supervison case.

Similar to a supervisory policy, restricting the speed at which autonomous machines can operate reduces net returns. A speed restriction decreases the profitability potential more than a supervisory policy and jeopardizes the economic viability of autonomous machinery for the scenario where no yield increases or cost reductions exist. Furthermore, restricting speeds increases the optimal number of autonomous machines and influences the production practices for corn and soybeans. The increase in autonomous machines does not fully offset the speed reduction, resulting in untimely planting and a slight yield reduction.

Table 5 illustrates the impact of a combined supervisory (both individual machine and fleet) and a speed restriction policy. As expected, a combination of both policies has the greatest reduction in net returns. The coupling of policies results in three scenarios for which autonomous machinery is not an economically viable alternative to conventional machinery, relative to when only a supervisory policy is evaluated. The speed restriction would need to increase to 3.4 mph, from 2 mph for the cost only scenario when coupled with the fleet supervisory policy, for autonomous machinery net returns to equal conventional machinery and therefore induce the adoption of autonomous machinery. Similar to the stand-alone policy results, the optimal number of autonomous machines also increases, influencing both production practices and yields for corn and soybeans. For a fleet supervisory policy coupled with a 2 mph speed restriction, the optimal number of autonomous machines increases to five, compared to two under the unrestricted scenario.

For all scenarios, both a supervisory policy and a speed restriction policy will reduce the profitability potential and influence autonomous machinery's commercialization. Additionally, both fleet supervisory and speed restriction policies increase the capital expenditure required for autonomous machinery to be economically viable. Furthermore, production practices, specifically optimal planting dates, change due to these policies. However, these results could change based on farm size.

Shockley, Dillon, and Shearer (2019) illustrate that autonomous machinery has the potential to be more profitable at smaller farm size (< 500 acres). Smaller farm sizes can capture economies of size in their operation with autonomous machinery, traditionally afforded to larger farming operations. Therefore, to address objective four, this study examines both a 500-acre and a 3,000-acre farm to determine if supervisory and speed restriction policies affects autonomous machinery's economic feasibility. For the 500-acre farm, in the baseline no regulation scenario autonomous machines are more profitable than conventional machinery for all benefit cases examined. Compared to conventional machinery, the increase in expected net returns for autonomous machinery without supervisory requirements or speed restrictions ranges from 11% to 29% for the 500-acre farm, depending on the anticipated yield and cost benefits.

The smaller farm has more to gain from autonomous equipment than the 2100-acre baseline farm. For the 500-acre farm in the baseline no regulation scenario, autonomous equipment increases per acre net returns by almost $33/acre, but for the 2100-acre farm that autonomous equipment advantage is only about $14/acre. The 2100-acre farm has a cost of production advantage due to economies of scale, but in that scenario, autonomous equipment narrows the 2100-acre farm economies of scale net return advantage from about $27/acre to only slightly more than $7/acre.

When either supervisory regulations or a speed restriction is included, expected net returns decrease, reducing autonomous machinery's economic viability compared to conventional. However, the implications of supervision and speed regulations are slightly better supported by the 500-acre farm compared to the 2,100-acre farm becaasue the 500-acre farm has more to gain from autonomous equipement. For example, if on-site supervision is required and speed restrictions are imposed, expected net returns are higher with conventional human operated equipment for both the 500-acre and 2,100-arce farms. However, with a 10% cost savings from reduced input use the 500-acre farm is better off with autonomous equipement, whereas the 2100-acre farm still favor conventional equipment. With both yield and cost benefits included, and both speed restriction restrictions and per machine on-site supervision, the autonomous equipment advantage for the 500-acre farm is $43.30/acre, but for the 2100-acre farm it is only $17.92/acre. Furthermore, a fleet supervisory regulation combined with a speed restriction increases the optimal number of autonomous machines for the 500-acre farm from one to two, hence increasing capital expenditures. Unlike the 2,100-acre scenario, this increase in the number of autonomous machines did not influence corn and soybeans' production practices. Overall, the smaller farm has more flexibility in supporting the supervisory regulations and speed restrictions because it gains more from the use of autonomous machinery than the larger farm.

The larger farm size examined (3,000 acres) has similar results to the 2,100-acre farm scenario. All supervisory policies and speed restriction scenarios examined reduced the profitability of autonomous machines compared to conventional machines. Furthermore, autonomous machines are not an economically viable alternative to conventional if no anticipated benefits are experienced for autonomous machine usage when a speed restriction regulation is in place, alone or coupled with either supervisory policy. Likewise, autonomous machines are not economically viable if only a cost reduction benefit occurs and a speed restriction coupled with a per machine supervisory policy exist. Furthermore, both policies increase the optimal number of autonomous machines compared to the unrestricted case. Unlike the 2,100-acre farm scenario, a fleet supervisory policy affects the production practices for corn and soybeans. If a speed restriction exists, the optimal number of autonomous machines is six, compared to two when only a per machine supervisory policy exists. Similar to the 2,100-acre farm, the increase in autonomous machines due to the policies impacts the production practives for corn and soybeans.

Conclusions

While autonomous equipment is on the verge of commercialization in the U.S., policies restricting operational speed or mandate supervision would directly affect this technology's economic viability and hinder adoption. This policy evaluation indicates that individual machine supervision decreases expected net returns of autonomous machinery more than a fleet supervisory policy. Under specific scenarios, autonomous machines are no longer an economically viable alternative to conventional machinery if an individual machinery supervisory policy is enacted. Furthermore, supervisory policies increase the optimal number of autonomous machines required to perform grain production activities and influence the optimal production practices for corn and soybeans. If stringent supervisory time and speed regulations are adopted, autonomous equipment is only profitable with substantial yield improvements and variable cost savings. These policies increase the urgency of research to measure how small autonomous equipment reduces soil compaction and improves soil health, and accurately quantify input reduction from site-specific applications.

Speed restrictions reduces the profitability potential of autonomous machinery in grain crop production in the U.S. more than a supervisory regulations. Like a supervisory regulation, a speed restriction will increase the number of optimal autonomous machines required and affect production practices. While speed and supervisory regulations are intended to aid in safe operations of autonomous machinery in production agriculture, policymakers need to understand the farm level's economic implications. Implementing such policies will affect autonomous machinery's commercial viability, require larger capital investment at the farm level, and influence production practices. Furthermore, speed and supervisory regulations will influence adoption based on farm size. Results herein indicate that smaller farm sizes are influenced less by these regulations compared to larger grain farms. This is attributed to the greater profitability potential of autonomous equipment on smaller farming operations and their ability to absorb the economic ramifications caused by both regulations.

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Table 1. Conventional machinery options considered for comparing against autonomous machinery to conduct traditional grain production activities in Kentucky.

Tractor (hp)	105, 130, 190, 300, 400
Sprayer (broadcast, feet)	27, 40, 50, 60, 90, 120
No-till split-row planter	4-row, 6-row, 8-row, 12-row, 16-row, 24-row
Nitrogen applicator	6-row, 8-row, 12-row

Source: Shockley, Dillon, and Shearer (2019)

Table 2. Autonomous equipment specification based on the HFH example.

	Tractor	Planter [a]	Sprayer	Spinner Spreader
Purchase Price	$31,648	$34,600	$6,370	$4,550
Implement Specifications				
Base Speed (mph)		5	8	8
Width (ft.)		10	13	40
Efficiency (%)		70	70	70
Performance Rate (acres/hour)		4.2	8.8	27.2
Repairs and Maintenance [ab]	40%	50%	20%	20%
Useful Life (years)	20	10	10	10
Annual Usage (hours)	600	150	200	150

[a] Planter substituted for the drill used by the HFH project to adapt equipment set for US corn and soybean cropping system. Planter cost and specifications based on the Mississippi State Budget Generator.

[b] Repairs and maintenance is reflected as a percent of purchase price over the total useful life of the equipment

Table 3. Economic and machinery selection results for various anticipated autonomous machinery benefits under no policy restrictions for a 2100-acre grain farm.

Conventional Machinery Expected Net Returns[1] = $691,278

Yield Increase[2]	Cost Reduction[3]	Autonomous Machines	Expected Net Returns (N.R.)[1]	N.R. Diff. from Conventional
No	No	2	$719,806	4.1%
No	Yes	2	$749,551	8.4%
Yes	No	2	$805,596	16.5%
Yes	Yes	2	$835,341	20.8%

[1] Returns to land, management, overhead labor and other overhead expenses

[2] 7% yield increase due to reduced compaction

[3] 10% cost reduction on selected production inputs (herbicide, insecticide, seed, and nitrogen)

Table 4. Economic and machinery selection results for various anticipated autonomous machinery benefits under an individual machine supervisory policy, fleet supervisory policy, or a speed restriction for a 2100-acre grain farm.

Supervisory Policy	Yield Increase[1]	Cost Reduction[2]	Autonomous Machines	Expected Net Returns (N.R.)[3]	N.R. Diff. from Conventional
Machine	No	No	2	$702,027	1.6%
Machine	No	Yes	2	$731,772	5.9%
Machine	Yes	No	2	$787,818	14.0%
Machine	Yes	Yes	2	$817,563	18.3%
Fleet	No	No	3	$711,813	3.0%
Fleet	No	Yes	3	$741,558	7.3%
Fleet	Yes	No	3	$797,604	15.4%
Fleet	Yes	Yes	3	$827,349	19.7%

Speed Policy	Yield Increase[1]	Cost Reduction[2]	Autonomous Machines	Expected Net Returns (N.R.)3	N.R. Diff. from Conventional
2 mph	No	No	4	$676,530	-2.1%
2 mph	No	Yes	4	$706,275	2.2%
2 mph	Yes	No	4	$761,927	10.2%
2 mph	Yes	Yes	4	$791,672	14.5%

[1] 7% yield increase due to reduced compaction

[2] 10% cost reduction on selected production inputs (herbicide, insecticide, seed, and nitrogen)

[3] Returns to land, managemenet, overhead labor and other overhead expenses

Table 5. Economic and machinery selection results for various anticipated autonomous machinery benefits under an individual machine or fleet supervisory policy restriction coupled with a 2 mph speed restriction for a 2100-acre grain farm.

Supervisory Policy	Yield Increase[1]	Cost Reduction[2]	Autonomous Machines	Expected. Net Returns (N.R.)[3]	N.R. Diff. from Conventional
Machine	No	No	4	$613,850	-11.2%
Machine	No	Yes	4	$643,595	-6.9%
Machine	Yes	No	4	$699,159	1.1%
Machine	Yes	Yes	4	$728,904	5.4%
Fleet	No	No	5	$663,185	-4.1%
Fleet	No	Yes	5	$692,930	0.2%
Fleet	Yes	No	5	$748,617	8.3%
Fleet	Yes	Yes	5	$778,362	12.6%

[1] 7% yield increase due to reduced compaction

[2] 10% cost reduction on selected production inputs (herbicide, insecticide, seed, and nitrogen)

[3] Returns to land, managemenet, overhead labor and other overhead expenses