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The Impact of Swarm Robotics on Arable Farm Size and Structure in the UK

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Abstract

Swarm robotics has the potential to radically change the economies of size in agriculture and this will impact farm size and structure in the UK. This study uses a systematic review of the economics of agricultural robotics literature, data from the Hands Free Hectare (HFH) demonstration project which showed the technical feasibility of robotic grain production, and farm-level linear programming (LP) to estimate changes in the average cost curve for wheat and oilseed rape from swarm robotics. The study shows that robotic grain production is technically and economically feasible. A preliminary analysis suggests that robotic production allows medium size farms to approach minimum per unit production cost levels and that the UK costs of production can compete with imported grain. The ability to achieve minimum production costs at relatively small farm size means that the pressure to "get big or get out" will diminish. Costs of production that are internationally competitive will mean reduced need for government subsidies and greater independence for farmers. The ability of swarm robotics to achieve minimum production costs even on small, irregularly shaped fields will reduce pressure to tear out hedges, cut infield trees and enlarge fields.

Keywords: *Swarm robots; economy of size; grain production.*

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1. Introduction

Robotic agriculture is widely predicted by researchers, academics and business (see for example, Robotic Business Review, 2016; Shamshiri *et al.*, 2018; Duckett *et al.*, 2018), but rigorous economic analyses of the economic feasibility of robotic farms are rare. One common element of most visions of robotic agriculture is that removing human equipment operators will lead to a radical redesign of agricultural mechanization. With no human operator, the economic motivation for the ever-increasing size of farm equipment almost disappears and farming with swarms of smaller robots become an attractive alternative. Economic analysis of crop robotics is rare primarily because it is early days for this technology. Most public sector research on crop robotics is at most in the prototype stage without out enough field experience to make credible economic estimates. Private sector crop robots are proprietary technology and little information is released. This economic analysis is made possible through the experience of the Hands Free Hectare (HFH) demonstration project at Harper Adams University which showed that small to medium scale conventional equipment would be retrofitted for autonomous field crop production (Gough, 2018). The HFH model is swarm robotics in the sense that it potentially uses multiple smaller machines to accomplish what a single large machine on conventional farms does. The overall objective of this study is to identify the implications of swarm robotics for farm size and structure in the UK. The methodology of this study uses information gathered in a systematic review of the economics of agricultural robotics literature, data from the HFH demonstration project which showed the technical feasibility of robotic grain production, and farm-level linear programming (LP) to estimate changes in the average cost curve for wheat and oilseed rape from swarm robotics. A timely ex-ante economic analysis is needed to: 1) help engineers and entrepreneurs identify the most profitable crop automation alternatives, 2) guide farmers in their decisions about using crop robotics, and 3) inform policy makers about the costs and benefits of crop robotics.

Farm LP models have long been used as a means for identifying the portfolio of enterprises and technologies that are the best way of using the farm resources (see e.g. Heady, 1954). This approach has distinct advantages over partial budgeting because (a) it can select a single plan that produces maximum net returns, and (b) it allocates the scarce resources (land, labour, machinery) of the farm so as to use them as efficiently as possible in the economic sense and (c) for complex farming operations it can quickly and efficiently sort through thousands of alternatives. Numerous books have addressed the subject (e.g. Hazell and Norton, 1986; Kaiser and Messer, 2011), and these models can be adapted for use with farms that include both crop and livestock enterprises (e.g. Morrison, *et al.*, 1986). A survey of applications of these types of models can be found in Glen (1987).

Similar farm planning models have been widely used to determine the potential of crop and livestock technology options worldwide. McCarl *et al.* (1974) describe a model used to help US farmers sort through the genetic, mechanical and chemical technologies that became available in the 1960s and 1970s. Audsley (1981) developed a UK farm LP for evaluation of new machines and farming techniques. Audsley and Sandars (2009) summarize the use of LP and other operations research models in analysis of UK agricultural systems. In recent years farm LP has been used in the UK mainly to identify the most cost-effective environmental management options (e.g. McLeod *et al.*, 2010; Williams *et al.*, 2003; Annetts and Audsley, 2002). Brandao *et al.* (1984) used LP in analyzing cropping options in Brazil in the 1970s and 1980s. In Africa they have been used to identify likely agricultural development pathways (e.g. Abdoulaye and Lowenberg-DeBoer, 2000). Sanders and students analyzed technology and crop alternatives for cotton producers in West Africa (Coulibaly *et al.*, 2015; Baquedano *et al.*, 2010; Cabanilla *et al.*, 2005; Vitale and Sanders, 2005; Vitale *et al.*, 2008). Other applications have used these techniques to evaluate management options for dairy farming in Costa Rica (Herrero, Fawcett and Dent, 1999) and for evaluating cattle production systems in Venezuela (Nicholson *et al.*, 1994).

Farm LP models can also be used to understand the role of risk in farm decision making. Research with mathematical programming models found a limited role for risk aversion in Midwest U.S. agriculture (Brink and McCarl, 1978). Rather than account for risk aversion directly, it has been common practice to handle these through chance constraints for available good field time (Charnes and Cooper, 1959; Kaiser and Messer, 2011). The HFH-LP uses this good field days approach to modeling risk.

While robotics is well established in industrial livestock production, particularly dairy, the use and the economic analysis of autonomous machines for crop production is at its early stages (Lowenberg-DeBoer *et al.*, 2018). Most studies of the economics of crop robotics use partial budgeting methods and focus on automation of one crop operation (e.g. weeding, harvesting). Lowenberg-DeBoer *et al.* (2018) found only three studies that attempted to consider a systems analysis of the economics of crop robotics. The most successful systems analysis is by Shockley *et al.* (2019) who employed an LP model to analyse the economics of using autonomous equipment for maize and soybean production in Kentucky USA. They assumed that all in-house field operations are potentially autonomous, but assumed that contractors would undertake phosphorous and potassium fertilizer application, lime spreading and harvest with conventional equipment operated by human drivers. Parameters for autonomous equipment was based on prototypes developed and tested by their colleagues in the Department of Biosystems and Agricultural Engineering at the University of Kentucky. The analysis compared net returns from using autonomous equipment to the best complement of conventional equipment for a given farm size. The conventional tractor options range from 105 hp to 400 hp. The conventional sprayer alternatives in the model ranged from 8.2 m to 36.6 m. Because autonomous equipment for grain production is not yet on the market and the cost of this equipment is unknown, Shockley and Dillion (2018) argue that they cannot determine if autonomous machines would be more cost effective than conventional mechanization. They reported their key results in terms of the breakeven price of computerized controls that would convert conventional tractors to autonomous. The analysis suggested that relatively small autonomous equipment would have economic advantages for a wide range of farm sizes, but especially for small farms.

This analysis is able to go beyond Shockley *et al.* (2019), mainly because the HFH showed that it is possible to use commercially available Global Navigation Satellite Systems (GNSS) and drone autopilot software to retrofit conventional medium scale farm equipment for autonomous operation. The cost and reliability of GNSS, drone software and conventional farm equipment is known and consequently it is possible to estimate the cost of autonomous field crop equipment. This estimate is particularly relevant because in the transition from conventional to robotic field crop production retrofitted equipment would probably be used initially. Specially designed autonomous equipment would come later. The HFH analysis also goes beyond Shockley and Dillon to automate all production activities, including fertilizer and lime application, and harvesting.

The overall objective of this study is to identify the implications of swarm robotics for farm size and structure in the UK. The specific objectives are to:

1) Estimate the economic feasibility of field crop robotics for UK agriculture,
2) Show how field crop robotics shift the shape of the UK wheat production cost curve, and
3) Identify the implications of this cost curve change for the size and structure of farms in the UK.

The hypothesis is that with swarm robotics the UK grain production cost curve would change in two key ways: 1) the cost curve would fall more rapidly for smaller farms and arrive at minimum cost at a smaller farm size than is currently the case, and 2) the UK grain cost curve minimum cost would be closer to (and perhaps below) the import substitution price level.

2. The Model

The HFH-LP model was based on a well tested and particularly flexible system for model farming operations known as the Purdue Crop/ Livestock Linear Program (PC/LP) (Preckel *et al.*, 1992; Dobbins *et al.*, 1990; Dobbins *et al.*, 1992; Dobbins *et al.*, 1994). This model accommodates both crop and livestock production, taking into account the use of crop outputs as feedstuffs. Crop modeling allows for sole crops, multi-year crop rotations, and multiple cropping – the raising of more than one crop on the same piece of land within the same year. Categories of resources can be distinguished including owned and hired labour, plots of land with different soil types, and different types of livestock facilities. This system was used from the mid-1990s through to about 2010 as an analytical tool for Purdue's Top Crop Farmer Workshop. Farmers from across the Midwestern United States came to Purdue each summer and developed linear programming models for their farms to evaluate alternative technologies and resource investments. An updated version of the PC/LP system has been developed in the General Algebraic Modelling System (GAMS, 2019) modeling language. This GAMS version was used by the Purdue University Orinoquia Initiative to help the government of Colombia evaluate proposals for agricultural development in the Orinoco River basin. Orinoquia LP model is described at by Preckel *et al.* (2017) and Fontanilla (2017). The HFH-LP model is a modified version of the PC/LP model using the GAMS, software. In many ways the HFH-LP is similar to the Audsley (1981) UK farm LP, but taking advantage of more recent software.

The HFH-LP model can be expressed in the standard summation notation used by Boehlje and Eidman (1982) as:

$$Max\ \Pi = \sum_{j=1}^{n} c_j X_j \tag{1}$$

subject to:

$$\sum_{j=1}^{n} a_{ij} X_j \le b_i \text{ for } i = 1 \ldots m \tag{2}$$

$$X_j \ge 0 \text{ for } j = 1 \ldots n \tag{3}$$

where:

X_j = the level of the *j*th production process or activity,

c_j = the per unit return (gross margin) to fix resources (b_i's) for the *j*th activity,

a_{ij} = the amount of the *i*th resource required per unit of the *j*th activity

b_i = the amount of the *i*th resource available.

The gross margin (c_j's) is total crop sales revenue minus total direct costs, and can be considered returns to fixed costs. In other words net returns from the operation equals gross margin minus fixed costs. Government subsidies are not included in this calculation. In the HFH-LP analysis, the objective function was to maximize gross margin for each set of land, operator labour and equipment. This is a computationally simpler formulation than the integer programming employed by Shockley and Dillon (2018) who include equipment selection within the model. Fixed costs are land, farm facilities, equipment, and compensation for management, risk taking and labour provided by the operator.

Because crop yields depend on the crop grown the previous season, and timing of planting and harvest, the production activities are modelled as rotations with specific plant and harvest time combination. For instance, a two crop rotation activity (an Xj) might have both crops planted and harvested at their optimal times. Another activity might have both crops planted and harvested later than optimum. Yet another activity might have one crop planted early and the other late. The model uses a simplifying assumption of "steady state" in that it assumes the selected rotations are repeated indefinitely.

Because agricultural activities are often seasonal, the choice of time step is crucial. The HFH-LP assumes a monthly time step. This is a compromise between accurate modelling of the seasonal pattern of work and need to keep the model relatively simple. A quarterly time step would be too coarse; there is an important difference between harvesting oilseed rape (OSR) in July and October, or planting wheat in September or November.

Because of rain and inclement weather, crop activities are constrained to the number of days each month when field work is possible, which is substantially less than the number of calendar days in the month. In each month the number of good field days can be estimated based on meteorological data. The primary mechanism for modelling risk aversion in the model is the level of probability assumed for the good field days. The standard PC/LP assumption was to use the good field data available in the 17th worst year out of 20 (McCarl *et al.*, 1974). This would be the number of good field day available 85% of the time. The Agro Business Consultants (2018) provide estimates of the number of good field days available in 4 years out of 5 (i.e. 80%). Conventional machine scenarios assume that most field operations occur during daytime (i.e. on average about 10 hours per day). The robotic scenarios assume that the autonomous tractors can work 22 hours per day with 2 hours for repair, maintenance, and refuelling, however, grain harvesting is limited by nightime dew to 10 hours per day.

The primary constraints are:

- *Land* – The sum of land used in production activities is less than or equal to the arable land available. If *q* crops are in a given rotation, the land used for a unit of a rotation is the fractional unit *1/q* of each crop. For example, one hectare of a wheat-oilseed rape rotation is equal to half a hectare of wheat and half a hectare of OSR.
- *Human Labour* – the sum of the labour needed in each month for each crop in the rotation multiplied by the fractional unit (*1/q*) of each crop in a given rotation. The sum of the human labour required must be less than the labour available from the operators, permanent farm labour, and temporary farm labour on the number of good field days. Based on HFH experience, human supervision of robotic labour is assumed to require 10% of the machine time in the field.
- *Machine Time* – In some cases, the time per day available for certain crop machine operations may be more limited than human operator time. For example, in good weather tillage or plant activities might continue around the clock if humans work in shifts, but, because of dew in the UK, combine harvesting of small grains and oilseeds can usually occur only from mid-morning to dusk. The machine time constraint is that the sum of machine time per crop in a given month on good field days, weighted by the rotation fraction (i.e. *1/q*), must be less than or equal to the amount of machine time available. In the analysis of robotic crop production the machine time is robot time required for each crop rotation in each month.
- *Cashflow* – sum of the variable costs for each crop in a rotation in a given month multiplied by the rotation fraction must be less than or equal to the working capital available. In the baseline analysis this constraint is not binding.

To focus on the essentials the initial HFH-LP is specified with a very simple crop rotation and using standard cost estimates from the Nix Pocketbook (Redman, 2018) and The Agricultural Budgeting & Costing Book (Agro Business Consultants, 2018). The primary rotations modelled were winter wheat-oil seed rape (OSR) with a range of timeliness of planting and harvesting. Spring barley-OSR rotations with several timeliness alternatives were included to give the model some flexibility in the timing of field operations. Field operation timing is drawn from Finch *et al.* (2014) and Outsider's Guide (1999). Equipment timeliness estimates and other machine relationships are from Witney (1988). All crops are assumed to be direct drill. Key baseline assumptions are described by Lowenberg-DeBoer *et al.* (2019).

3. Baseline Results

To help explore the implications of the baseline model results solutions were generated for each of the following farm sizes assuming all are 90% arable:

- A 66 ha farm - This is the average farm size in the West Midlands of the UK (DEFRA, 2018a).
- A 159 ha farm - This is the average size of cereals farms in England (DEFRA, 2018b).
- A 284 ha farm– This is the average size of cereals farms over 100 ha in England (DEFRA, 2018b).
- A 500 ha farm - This is an arbitrary larger farm size.

And equipment sets:

- HFH sized equipment (38 hp tractor) with human drivers.
- HFH autonomous equipment (38 hp tractor).
- Smaller conventional equipment (150 hp tractor).
- Large conventional equipment (300 hp tractor).

Summaries of the initial solutions are presented in Table 1. The solutions listed plant the entire arable area because in normal circumstances farmers will prefer a plan that uses their entire resource base. The solutions assume one full time operator, temporary labour available on an hourly basis, and that conventional equipment is typically operated at up to 10 hours per day. The "X2, X3, X4" in the scenario name indicates the number of equipment sets that are needed to farm the specified area. For example, "AutonomousX3" means that it requires three sets of the HFH equipment to farm the 450 arable ha under the assumptions used.

Table 1 shows that under the assumptions used, the small conventional equipment is quite profitable, but it requires substantial amounts of hired labour. While tractor drivers are easier to hire in the UK than workers for hand weeding, vegetable harvesting or other farm manual labour, it is not obvious that the amount of labour needed could be hired at the average wage of £9.75/h assumed in this analysis. Because grain production is already highly mechanised it may be converted to robotic production more easily than horticulture where many production processes are still manual.

Table 1

Summary of Initial HFH-LP Solutions for Representative Farm Sizes with Temporary Labour Available

Scenario	Arable Area (ha)	Labour Hired (days)	Operator Time (days)	Gross Margin (£/yr)	Return to Operator Labour, Management and Risk Taking (£/yr)	Wheat cost of production with Operator Labour Cost Allocated (£/MT)
Conv. 38hp	59.4	0	79	47048	16888	166
Conv. 38hpX2	143.1	72	118	107759	38424	149
Conv. 38hpX3	255.6	195	144	187237	68043	139
Conv. 38hpX4	450.0	411	186	302920	103481	136
Autonomous	59.4	0	26	47048	16149	133
Autonomous	143.1	8	54	112691	50739	122
AutonomousX2	255.6	50	62	198587	86036	119
AutonomousX3	450.0	121	76	347015	153479	115
Conv.150hp	59.4	0	28	47048	-26001	212
Conv.150hp	143.1	0	68	112243	8142	157
Conv.150hp	255.6	31	89	200017	54178	136
Conv.150hp	450.0	108	104	331989	63017	140
Conv.300hp	59.4	0	16	47048	-70973	288
Conv.300hp	143.1	0	39	113343	-35731	182
Conv.300hp	255.6	1	69	202371	11560	152
Conv.300hp	450.0	35	87	353677	90743	131

The small scale conventional equipment also requires the operator to spend a substantial amount of time driving a tractor or combine. If full time work is about 220 days per year, then the 450 arable hectare farm would require the operator to spend 85% of his or her time operating equipment, leaving very little time for management, marketing and other farm tasks.

With the assumption that supervision of the autonomous equipment requires about 10% of the equipment field time, the total operator time commitment to crop operations is roughly similar to that of the scenarios with large conventional equipment. Experience will show whether the 10% supervision time based on HFH experience is typical of other robotic farms.

For the robotic farming scenario the bulk of the human time is devoted to hauling grain from the field to the farmstead or market during harvest in July, August and September. For example, in the 284 ha robotic farm scenario, 45% of the annual operator time and all of the hired labour is devoted to grain hauling from the field to the farmstead or market. This hired labour represents a cash cost of £7724, but even more important than the expense is the difficulty of filling this harvest time spike in labour demand. This suggests that one technical priority for robotic farming should be to develop a system in which either the grain transport from field to farmstead/market is automated (i.e. self-driving lorries), or where grain is stored in the field until it is used or goes to market.

While most of the discussion of the economics of crop robotics has been focused on reducing the human labour requirements and cost, this analysis suggests that there may be an equally important impact on equipment investment costs. The equipment investment for the large conventional farm is estimated at £723,500 and for the conventional farm with the 150 hp tractor £389,500. This assumes the purchase of new equipment. The estimated new equipment investment for one set of the robotic equipment is £64,750, with £4850 of that being the RTK GNSS and modified drone software. For the 450 ha farm, the equipment investment for the robotic farm is £194,250 (three sets of the HFH equipment) or only 27% of the estimated investment for the 296 hp tractor conventional farm, which provides the minimum wheat production cost among conventional alternatives. By more intensively using smaller equipment the robotic farm is able to substantially reduce capital costs.

Because the direct costs and yields are assumed to be the same across all scenarios, the gross margins are similar at each farm size. For the smallest farm, gross margins are identical for each equipment scenario (i.e. £47,048) because all four equipment scenarios are able to plant and harvest the wheat/OSR rotation in the optimal period. For the larger farms the gross margin differences occur because: 1) some planting and harvesting occurs in non-optimal months, 2) equipment and labour constraints force less profitable spring barley into the crop mix (see the Autonomous scenario for the 255.6 ha arable farm), and 3) some solutions use more temporary labour.

In this analysis the return to operator labour, management and risk taking is highest for the autonomous equipment, except for the small scale conventional equipment on the smallest farm. This occurs because the operator is assumed to be full time on the farm (i.e. operator compensation is not deducted from the return estimate) and because of the added investment to retrofit the equipment for autonomous operation. For the larger farms the autonomous scenario has the highest return to the operator.

The cost of wheat production is estimated because much of the debate in economics about farm economies of size is in terms of cost of production (Miller *et al.*, 1981). Economic theory indicates that farms which operate at the farm size with the lowest unit cost of production will be more successful and over time the structure of the farming industry will tend toward that lowest unit cost of production farm size (Miller *et al.*, 1981; Hallam, 1991; Duffy, 2009).

Economic research in the 1960s and 1970s in North America suggested that for many farm products the long run average cost curve is "L" shaped. Unit costs are high on small farms. Those costs fall as farm size grows until the long run average cost curve levels out at minimum cost. This research argues that a range of farm sizes are observed because the bottom of the cost curve is nearly flat. It has been hypothesized that the cost curve would eventually rise for very large farming operations because of diseconomies of scale, but in practice that has not been widely observed with conventional crop technology. The key empirical issue is at what farm size is that minimum cost achieved? The hypothesis is that autonomous equipment would allow a farmer to achieve minimum cost at a smaller scale than conventional equipment would. In terms of the cost curve, this means that the robotic farm cost curve would arrive at a relatively flat bottom at a smaller scale than the conventional cost curve.

The wheat production cost estimate includes all direct costs and indirect costs for machinery, farm infrastructure and operator compensation prorated to the time devoted to field activities, plus 20%. The extra 20% is assumed to be needed for management and marketing. The operator compensation estimate is from the 2016 Farm Manager Survey (Redman, 2018, p. 166). That estimate is £52,238 in monetary compensation, plus £12,530 in non-cash benefits including rent free accommodation, mobile phone and use of a motor vehicle. The sum is a total of £64,768.

A chart of the wheat production costs estimated using HFH-LP takes an approximate "L" shape (Figure 1) with the cost curve for autonomous equipment below the conventional cost curve. That figure assumes that for conventional equipment, farmers will choose the equipment size that minimizes the cost, so the conventional curve is at the minimum cost over the three equipment scenarios. The conventional and autonomous equipment cost curves have similar shapes, but that may be because of costs are estimated for a very limited number of equipment scenarios. If there were more equipment scenarios, the estimate would be more likely to pick up differences in the cost curve shape. Assumptions about allocation of farm operator time and costs may also affect the shape.

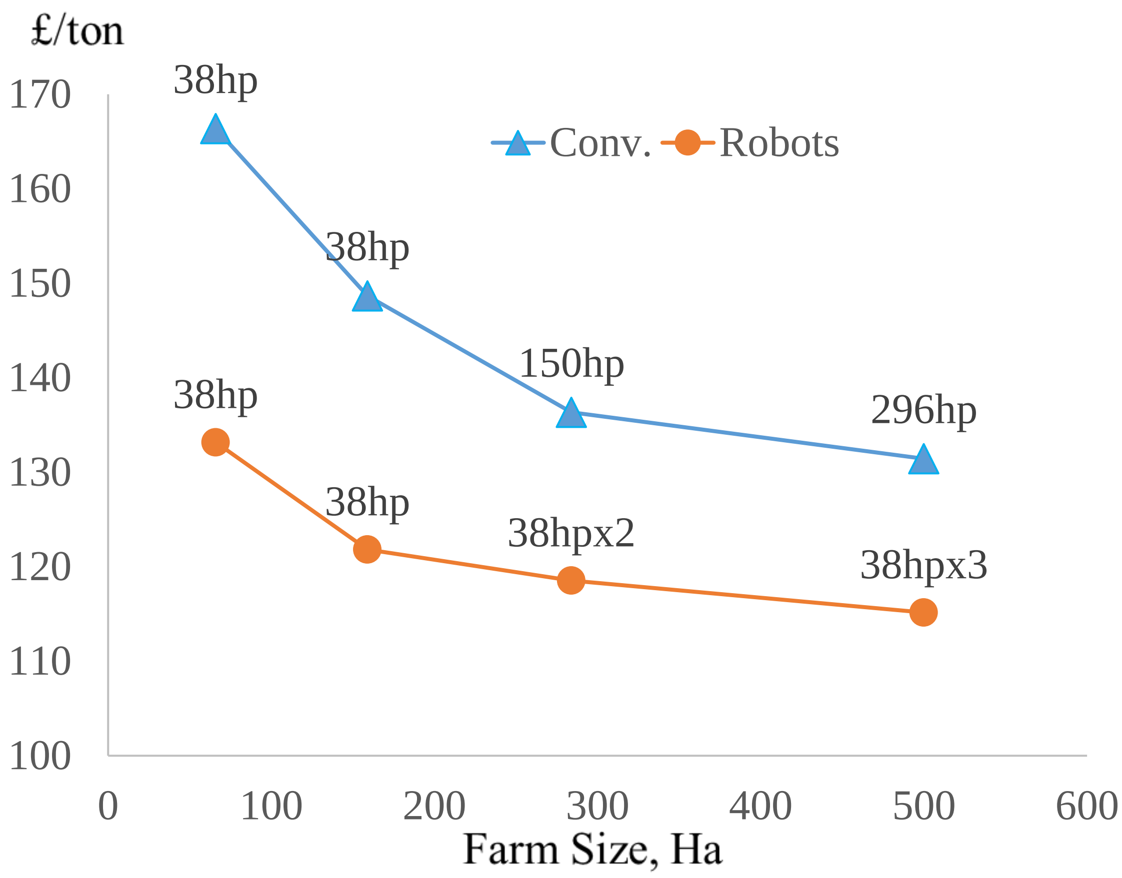

Figure 1. Wheat Unit Production Cost (£/ton) for Farms Equipped with Conventional or Autonomous Machines across a Range of Farm Sizes and with Operator Labour Cost Allocated

International comparisons of agricultural costs of production are fraught with difficulties because of exchange rates, explicit and implicit government subsidies, differing production practices, quality differences and other factors, but the *agri benchmark cash crop network* (http://www.agribenchmark.org/home.html) has attempted to estimate comparable costs for major production countries. Balieiro (2016) presented wheat production costs for 2008-2015 eight countries that, except for Russia and Ukraine, range from £123-£192/ton (GBP=US$1.30) with UK costs of production at the upper end of that range. Estimates for Russia and Ukraine are as low as £62-£77/ton. Most of recent UK wheat imports were from Canada, Germany and France with costs of production estimated between about £123 and £154/ton. With wheat cost of production on the robotic farm under £120/ton, UK wheat would be much more competitive with imported wheat than the conventional farm product. Analysis is needed to determine if other UK farm products would be more internationally competitive with robotic production.

The HFH-LP also provides information on the marginal values or "shadow prices" of the various farm resources. For example, the HFH-LP for the Autonomous scenario for the 284 ha farm shows that tractor time is binding in October and November during drilling of winter crops. The maximum number of eight hour tractor work days available in October is 52.25 (=19 good field days x 2.75 workdays per field day if working 22 hours per day). The maximum number of eight hour tractor work days available in October is 41.25 (=15 good field days x 2.75 workdays per field day if working 22 hours per day). The shadow value of tractor time is £623.72/work day; that means the gross margin could be increased by £625.72 if one more eight hour day of autonomous tractor time would be found. The shadow value of November tractor time is lower; it is only £41.81/workday reflecting the lower average yields and profits if wheat is planted in November rather than October.

Similarly, combine time is binding in July and August for the Autonomous scenario for the 284 ha farm. The shadow value of combine time in July is £1486.64/work day and in August £1377.96/workday. As with the tractor, the units are eight hour work days. Shadow prices can help technology developers target the highest value innovations.

4. Limitations

The HFH LP is a preliminary model of how robotics would affect field crop decisions in the UK. The analysis depends on several non-technical assumptions:

1) The ownership model of acquiring farm equipment services is relevant for autonomous machines. Service provider, rental and leasing approaches are widely discussed by robotics researchers and entrepreneurs.
2) Continuous on-site human supervision not required for the robotic farm. Currently, on-site human supervision of agricultural robots is required in some EU countries (e.g. Germany) and is required in the UK for drones. An on-site supervision requirement removes much of the cost savings for the robotic farm.
3) Insurance is available for the robotic farm at comparable cost to conventional farms.
4) Commercial manufacturing and sale of robotic equipment achieves economies of scale.

The HFH LP could be improved in many ways, including:

- Adding potatoes, sugar beets, field beans, peas, silage maize and other field crops commonly grown in the UK and including tillage options. Currently, only direct drill planting is modelled.

- Including annual vegetables (e.g. broccoli, cabbage, carrots, parsnips, lettuce). This would require information on the robotic harvesting equipment that is currently in prototype stage.
- Developing forage and grazing livestock activities. While milking robots and other autonomous machines are being used by intensive dairy farms, there is relatively little experience with robotics for grazing based livestock enterprises.
- Creating a model with organic field crop, vegetable and livestock activities. One of the primary constraints to expansion of organic production in the UK and other parts of the industrialized world is labour. The hypothesis is that robotics would reduce the cost of organic production substantially. This would require information on automated mechanical weeding equipment that is now being commercialized.
- Exploring the impact of field size and shape on cost of production with conventional equipment and swarm robotics. The current analysis assumes a 70% field efficiency for both conventional and robotic equipment, but the hypothesis is that robots could operate more efficiently than large conventional equipment on small irregularly shaped fields.
- Estimating the impact of automation for large scale farm equipment. The current model assumes large scale farm equipment without GNSS. The hypothesis is that GNSS guidance systems can improve field efficiency for conventional equipment even with small irregularly shaped fields. Semi-autonomous master-slave technologies (e.g. Zhang *et al.*, 2010), autonomous chaser bins (Smart Ag, 2019) and other automation has the potential to improve productivity and reduce costs for large scale equipment.
- Revisiting the question of good field days. The field days used in the model were estimated in the 1960s and 1970s assuming large scale conventional equipment. Even with conventional equipment, climate change may have affected the number of days per month when equipment can be operated in the UK. The hypothesis is that with smaller, lighter autonomous machines it may be possible to do field work under slightly wetter conditions and cause less damage to the soil.
- Working with engineers to estimate the reliability, maintenance costs and useful life of small and medium sized farm equipment under autonomous use. Currently, most small and medium farm equipment is designed for relatively light duty on small and medium scale farms. Round the clock operation in autonomous mode may entail higher maintenance costs and shorter useful life.

- Testing scenarios in which driverless lorries or automated tractors with trailers can transport grain from the field to the farmstead or market.
- Estimating the economic potential for robotic individual plant or other intensive management schemes, including micro-dosing of pesticides and fertilizers.
- Refining modelling assumptions and parameter estimates as on-farm experience with autonomous equipment grows. Initial parameters that should be calibrated include: human supervision time requirements, field efficiency under different soil, field shape and field size.

5. Conclusions

This study provides the first rigorous economic analysis that supports the hypothesis that swarm robotics will dramatically alter the economic environment in which UK arable farms operate. The ability to achieve minimum production costs at relatively small farm size and with a modest equipment investment means that the pressure to “get big or get out” will diminish. This provides the opportunity for modest size grain enterprises to become profitable instead of being a lifestyle choice. With reducing the need for labour and equipment investment, those modest sized grain enterprises could be combined with livestock, on-farm value added activities or off farm employment to provide enough income for family needs. Costs of production that are internationally competitive will mean there is a reduced reliance on government subsidies for survival and greater independence for farmers. The ability of swarm robotics to achieve minimum production costs, even on small, irregularly shaped fields, will reduce the environmental impacts of grain production. It will reduce the pressure to tear out hedges, to cut infield trees and to enlarge fields, as well as maintain better soil structure and fertility.

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