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**Exploring the adoption of Precision Agricultural technologies: a cross regional study of EU farmers**

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## 1. Introduction

The prescient need for sustaining soil quality to maintain and extend productivity potential, whilst simultaneously supporting a range of ecosystems services, makes precision farming a possible pathway for meeting global ambitions towards food security (Gebbers and Adamchuck, 2010; Telabpour *et al*., 2015). Precision agricultural technologies (PATs) are a set of technologies that are aimed at the management of in-field heterogeneity (Stafford, 2000; Fountas *et al*., 2005; Reichardt and Jürgens, 2009; Aubert *et al*., 2012). A range of benefits have been aligned with the uptake of PATs and these have focused on improved resource use productivity, reduced input usage and cost, in particular labour and management time, with wider associated benefits from targeted application of agrochemicals and nutrients (Godwin *et al*. 2003; Silva *et al*., 2011; Kinred *et al*., 2015; Smith *et al*. 2013; Eory *et al*. 2015; Schimmelpfennig, 2016). PATs have been in development for the last 3 decades, since the commercialisation of global positioning systems and we can identify four differing technological hierarchies of PATs (Figure 1).

**Figure 1. Hierarchy of Precision Agricultural technologies**

These hierarchies imply different levels of user engagement and, by implication, the requisite farmer or operator skill and acquired learning needed to operate these technologies. A number of authors identify two major types of user engagement, based on their level of interaction and the learning investment needed by the operator (Griffin *et al*., 2004; 2005; Daberkow *et al*., 2003; Popp *et al*., 2002; Miller *et al*., 2017). They identify '*embodied knowledge technologies*' which require no additional skills for their operation, for example automated guidance systems which allows precise control of machinery in the field; and '*information intensive technologies'* which provide additional information that offer insights for decision making, but also require further investment, in terms of knowledge, software or analytical service support for data analysis, for example from variable rate application technologies.

The attraction to policy makers of PATs within the farming community is that they may allow a step change in productivity to meet food supply requirements under land constraints and an increased desire for environmental monitoring (Zarco-Tejada *et al*., 2014; Schrijver *et al*., 2016). The current policy framework for PATs, and precision farming generally, is diffuse. Schrijver *et al*. (2016) outline potential European policies which are affected or may have to change to accommodate adoption of PATS. These include environmental regulations and directives focused on air, carbon and water pollution; regional policy which accommodates both the integration of broadband and mobile data networks in rural and remote rural regions; and the potential for alternative employment within these communities from on-farm PAT adoption. Moreover, a whole tranche of industry wide policies, pertaining to food traceability, data access and storage, and intellectual property rights have to evolve if PATs are to become an intrinsic part of the fabric of future European farming. More indirect drivers, through tightening of the Nitrates directive, may encourage some farmers to use N-efficient agronomic measures or technologies, such as variable rate nitrogen applicators. Similarly, if policy shifts towards rewarding public goods generation then payment mechanisms may incentivise organisation and collection of environmental data for basing payment rates (Barnes *et al*., 2011; Helm, 2017).

PATs also challenges the farming population to change working practices, requires high initial capital investment and added maintenance costs. A range of services from different consultancies have emerged which are allied to farming and provide analysis of the intensive data collected by PATs and related satellite imaging technologies. This diversity of service provision might have a lock-in effect due to, for example the incompatibility between different components of PATs and, consequently, negatively affect the uptake of PATs (Aubert *et al*., 2012; Robertson *et al*. 2007). A further set of barriers emerge from the regulatory, technological and policy environment which may provide restrictions, e.g. on unmanned aerial vehicles or access to internet based services in remote rural regions, which hamper uptake for particular members of the farming community (CSA, 2015).

The aim of this paper is to understand the internal and external determinants of the adoption of PATs within a European cross-country setting. The first objective is to analyse the characteristics behind non-adoption compared to adoption of PATs, in order to assess the potential barriers towards uptake. Secondly, we assess the characteristics across an adoption transition, from an 'embodied knowledge' technology to an 'information intensive' technology. In so doing we aim to understand the institutional drivers behind greater uptake of PATs. This assessment will allow us to provide insights for future interventions of agricultural policy within Europe.

A number of studies have examined the current uptake of PATs and generally find low adoption levels. These show that uptake is partly dependent on region or the focus of the technology. However, available literature is mostly focused on certain states of the US and Australia where PATs uptake is well documented (e.g. Robertson *et al.*, 2007; Kingwell and Fuchsbichler, 2011; Holland *et al.*, 2013; Miller *et al.*, 2017). Within Europe, uptake rates are less well explored and available studies are focused on specific countries (Paustian and Theuvsen, 2016; Lencsés *et al.*, 2014; Kutter *et al.*, 2011; Lambert *et al*., 2015). Moreover, given the perceived potential of precision agricultural technologies, as a mechanism to meet both food production and environmental pressures, it would seem important to focus efforts on assessing the potential of precision agricultural technologies across regional farming systems. This will complement the ubiquity of US based studies and provide some perspective towards the role of PATs within the EU.

We focus our study on two different PATs, namely machine guidance as an 'embodied knowledge' technology and variable rate nitrogen application technology as the 'information intensive' technology. These are defined, and were presented to farmers, as below:

> Machine guidance: "*Guidance technologies are systems that pilot machinery using* Global Navigation Satellite Systems (GNSS)*. They enable farm machinery to follow straight lines to reduce overlaps and avoid gaps of the tractor and equipment passes. In order to use machine guidance systems, one needs a GNSS receiver in the tractor or mounted on the machinery and a light bar or a display on-board to provide driving direction. A more advanced option is to use machine auto-guidance systems (or auto-steering), which are integrated in the tractor's hydraulics and can directly take over steering operations*".
>
> Variable rate nitrogen application technology (VRNT): "*enable changes in the application rate to match actual need for fertiliser in that precise location within the field. The basic idea is that, according to an electronic map or sensors, a control system calculates the input needs of the soil or plants and transfers the information to a controller, which delivers the input to the location*".

We employ a survey across five European countries representing different levels of intensity of arable production in order to identify what factors may lead to uptake. Generally these represent more larger scale and intensive systems within Germany, the UK and the Netherlands, and smaller scale arable farming in both Belgium and Greece. A cross-regional perspective is valuable as it provides reliable information on what particular factors are common across the European Union and which are regionally specific.

## 2. Methods and Data Collection

*Conceptual Framework*

PATs represent the integration of specific technologies which serve multiple functions. Farm machinery is augmented with information processing technology, data collection, real-time analysis and visualisation algorithms to support management decision-making. Studies which concentrate on single aspects of these technologies, e.g. Aubert *et al*. (2012) utilise the theory of technology acceptance (Davies, 1985) to understand uptake of information technology applications in farming. However, PATs represent a bundle of benefits perceived by the adopter and most studies tend to take a more holistic approach to understand the external and internal aspects factors driving uptake (Lima *et al*., 2018). Tey and Brindal (2012) provided a synthesis of the major factors which determine uptake of PATs, mostly from US based studies and we modify their categories to make them applicable to European farming systems. Figure 2 shows the hypothesised relationships between the internal and external variables relevant to the two PATs explored here.

**Figure 2. Hypothesised Relationships between the variables and the two adoption states**

*Respondent characteristics*

Formal education and age have been found to be significant predictors of adoption (D'Antoni *et al*., 2012; Pierpaoli *et al*., 2013; Torrez *et al*., 2016). These are common indicators of risk taking or innovative behaviour for most studies of technology adoption and seem to support the notion that younger and formally educated farmers are more likely to adopt PATs (Ascough *et al.* 2002; Tiffin and Balcombe 2011; Walton *et al*., 2010; Lawson *et al.* 2011). This is further evidenced by the lack of training and technical support perceived as an adoption constraint to uptake of precision agricultural technologies (Robertson *et al*., 2007; Reichardt and Jürgens, 2008).

*Structural and financial characteristics*

Studies on PAT adoption emphasise that adopters tend to operate a larger agricultural area, and subsequently generate a higher income (Fernandez-Cornejo *et al*., 2001; Cullen *et al*., 2013; Faber and Hoppe, 2013; Lawson *et. al*., 2011, Montalvo, 2008; Blackmore *et al*., 2006; Schimmelpfennig, 2016; Miller *et al*., 2017). This indicates the ability to accommodate some risk in investment of newer and larger technologies. Some studies identify owner-occupied farmers as more likely to adopt PATs, due to access to capital to enable investment in machinery (Putler and Zilberman 1988; Paustian and Theuvsen, 2016). Hence it may be that owner-occupiers have greater financial leverage to purchase capital heavy PATs compared to tenanted farmers, who rent land and therefore tend to not have the capital to borrow against for purchasing these equipment.

Farm and crop specialisation, inferred through the degree of income or the amount of land dedicated to specialised activities, are also potential predictors of adoption but these indicators are less common in the literature (Woodburn *et al.* 1994; Putler and Zilberman 1988; Castle *et al*., 2016), as has a focus on higher value crops (Blackmore *et al*., 2006). Adopters seem to have a greater number of regular labour employed, which is indicative of higher intensity of production (Paustian and Theuvsen, 2016). Regions with high labour cost have increased PAT uptake potential when land is relatively less costly (Swinton and Lowenberg-Deboer, 2001). In addition, Schimmelpfennig (2016) found unpaid farm labour, which is an opportunity cost, to be negatively associated with adoption of guidance systems and variable rate technology, as access to a large pool of family labour generally acts as a disincentive to uptake of technologies which are labour saving.

*Number of PATs adopted*

On-farm technological factors have also been found to predict adoption of PATs. Effectively, this infers that the presence of other technologies at the farm level will increase the probability to adopt the PAT (Griffin *et al*., 2017). Lambert *et al*. (2014) assumed PAT uptake to be a set of 'bundles' of technology which are contingent on adoption of other PATs. Miller *et al.* (2017) estimated Markov transitions of these adoption 'bundles' of PATs in a longitudinal dataset of Kansas farmers. They found that currently intensive adopters, defined as having three PAT technology bundles, were less likely to change adoption profiles compared to those which had adopted one or two bundles of PATs. Part of this they attributed to the attraction for data service providers who work with information heavy farmers (with more intensive bundles of technologies). This is because the farm is more likely to continue to provide specific data and therefore become more cost-effective for the data analysts.

*Influencers of adoption*

The use and perceived usefulness of consultants has been found to be positively linked to uptake of PATs (Reichardt and Jürgens, 2008). Better access to information has an effect on improving the overall attractiveness of the innovation. It also increases the knowledge of innovation implementation, reducing the uncertainty towards the potential benefits (Marra *et al.*, 2003). Hence, this can link to the use of advisors or consultants, but also infers membership of marketing co-operatives and machinery collective groups where information is passed through informal mechanisms, usually from farmer to farmer. Busse *et al.* (2014) explored the knowledge gap between different actors involved in PAT adoption, namely the input suppliers, dealers, farmers, scientists and policy makers. In a workshop study of German PAT stakeholders they found a gap in the transfer of knowledge between science and practice and, ultimately, limited communication and collaboration between farmers and technology providers.

*Attitudinal characteristics*

Economic profitability is a major concern when considering the adoption of any agricultural technology and the level of perceived profitability of adopting precision agriculture technologies has been found to dictate uptake (Olson and Elisabeth, 2003; D'Antoni *et al.*, 2012; Watcharaanantapong *et al.*, 2014; Castle, 2016; Schimmelpfennig, 2016). Robertson *et al.* (2007) and Montalvo (2008) identified knowledge gaps towards estimating the return on investment which leads to an inability to economically assess these technologies. A behavioural factor which has also been found to have a positive effect is the willingness of farmers to trust the technology. For example, a number of studies have found low levels of trust in the technology to be a key limitation for PATs adoption, relative to other factors (Mims *et al.*, 2005; Montalvo, 2008; Bogdanski, 2012; Eidt *et al.*, 2012).

*Regional characteristics*

Regional specific contextual factors, such as the presence of farmer co-operatives and the industrial structure of suppliers will determine the access to and availability of particular PATs. Accordingly, regional institutional factors will influence adoption (Paudel *et al.*, 2011; Lambert *et al.*, 2015).

*Data Collection*

In order to gather information on the potential for uptake of PATs a survey was conducted between August 2016 and February 2017 across five European countries (namely the UK, Germany, The Netherlands, Belgium and Greece). These countries were chosen to represent a diversity of different institutional structures (e.g. access to regional consultancy services), as well as structural factors (e.g. in terms of farm size and intensity of production) but also operating under a common European policy framework, all be it with regionalised approaches to regulation and reporting.

The sample was targeted at arable crop farmers and farm managers that were cultivating wheat, which is the arable crop most widely cultivated in Europe, covering 24% of the utilised agricultural area of arable land and accounting for 44.8% of the total cereal production in the EU (Eurostat, 2015), and/or potatoes (which is a high value crop, with a high economic output per ha per year), in the 2015/2016 cropping season. In Greece, cotton farmers were surveyed as a replacement for potatoes, as cotton is a main crop within Southern European states and potatoes are only marginally grown.

For sampling, farmers were stratified into 3 categories of technology adoption using definitions for the chosen PATs:

> i) Non-adopters: farmers who currently have not adopted MG only or VRNT bundled technology;
>
> ii) MG Only adopters: farmers who currently own or rent machine guidance, and;
>
> iii) VRNT bundle adopters: Farmers who currently own or rent both variable rate nitrogen technology and machine guidance. In order to operate VRNT, machine guidance is needed. For some farmers this is an addition to their current PATs while for others it comes as a complete bundle. Hence this choice reflects adoption of both technologies.

These were chosen to reflect a hierarchy of adoption from those disinterested or unable to engage in the technology to those heavily invested in PATs. Hence, some gradient could be drawn in order to quantify the differences across these three adoption groups. There are no specific representative databases on PAT adoption in Europe and we employed a multiple sampling approach as a means to create enough responses within these three categories. They were contacted through trade fairs, machine dealers, agricultural databases and personal contacts. Table 1 shows these by interview method, e.g. telephone, or face to face, and by contacting method.

**Table 1: Distribution of contact methods by region, number of individuals**

Table 2 outlines the key descriptive variables for the sample by each of the three adoption states. Differences emerge which reflect the diversity of case studies covering both Northern and Southern European Systems. The farmers managing larger areas in Germany and the UK shows average utilised agricultural area which ranges from around 200 ha up to over 1000 ha. The largest farm sizes were recorded for Germany, and this has some of the largest average agricultural areas in Europe (Eurostat, 2015). These regions, along with the Netherlands, are generally intensively managed arable systems. Both the Netherlands and UK have larger areas of potatoes grown, as they are principally the main growers of seed and ware producers in Europe (Eurostat, 2016). All countries have significant portions of land dedicated to cereals, again with the larger scale, more intensive, producers of wheat in the UK, Germany and the Netherlands. This intensity of production is reflected in the greater number of regular employees, in addition to farm family labour. Conversely, whilst only small average areas were identified, Greece has one of the largest agricultural labour forces within the EU (Eurostat, 2015) and this is reflected here, reflecting both cotton and cereals production. For most regions, as with previous studies on precision farming, non-adopters generally manage smaller areas than the adopters, but there is a more explicit increase in size characteristics between MG Only and VRNT bundle adopters.

**Table 2. Descriptive statistics of main land use and labour categories from the survey by region, mean and standard deviations**

*Data Analysis*

Common with studies of technology uptake most studies of PAT tend to take a General Linear Modelling approach and apply mainly multinomial logit or multivariate probit regression frameworks to examine the differences of influencing factors on a specific or a multiple set of technologies (Bannerjee *et al*., 2008; Paudel *et al*., 2011; D'Antoni *et al*., 2012; Torrez *et al*., 2016). A problem for cross-regional studies is how to accommodate for regional differences within a multinomial estimation framework. Applying dummy variables is inadequate when data are clustered by region, which will reflect the specific institutional characteristics outlined above and provide false standard errors. Accordingly, as our study covers five countries we propose a random intercept model. This allows us to control for the variation at both the regional level and the individual level.

Our analysis followed two complementary approaches. A multinomial approach (MLN) was used to estimate the determinants of adoption of the two technologies, as these are two different states of adoption (i.e. MG Only and VRNT bundle). The MLN covers more than two relative states of adoption, which would match the adoption profile observed here, and offers a relative estimate of the factors which determine adoption of MG Only compared to non-adoption, or the VRNT bundle compared to non-adoption. A binomial approach was then applied to the sub-sample of adopters in order to assess the factors that determine the adoption of the VRNT bundle compared to MG Only, which reflects the difference from an embodied knowledge technology to an information intensive technology.

A multilevel mixed-effects logistic regression framework was chosen to control for the influence of regional heterogeneity across the sample. A random intercept model, using the five regions as the level-2 nested clusters, was estimated to examine both variance at regional level and the influence of explanatory variables on determining uptake of PAT. The basic random intercept model is shown in Equation 1:

$$y_{ij} = (\beta_1 + \zeta_{1j}) + \beta_2 x_{ij} + \epsilon_{ij} \quad \text{(eq. 1)}$$

where $\zeta_{1j}$ is a random intercept indexed across the regional identifier (*j*). Hence, $\zeta_{1j}$ represents the deviation of region *j*'s intercept from the mean intercept $\beta_1$. Estimation was conducted using the GLLAMM package (Rabe-Hesketh *et al*., 2005) within Stata Version 15 (Stata Corp., 2017).

A logistic link model was used for the number of nominal outcomes, that is, (0) non-adoption, (1) MG Only, and (2) VRNT bundle. Thus, considering the range of outcomes (*y*), the predicted probability of the *i-th* farmer choosing a nominal outcome is (*y = 0,1,2*). This provides indications of the probability of a change in an independent variable (*x*) affecting membership of one of the three states of adoption. A binominal logistic regression simply reduces the nominal outcomes to a binominal structure (*y*=0,1).

The MLN regression estimates a set of binomial regressions between the base outcome state, in this case non-adoption, and the reference states, MG Only and VRNT bundle adoption. A total of 17 variables, grouped into 5 categories (Table 3) were selected, based on the conceptual framework above, to analyse the factors that we would expect to have some influence on adoption of precision agricultural technologies. Categorical responses were converted into dummy variables and are presented conditional on the reference value specified.

**Table 3. Variables used within the empirical model**

In order for efficient estimation some categories were compressed or converted into binary indicators, for example, education was reduced from a 6 point scale to a binary variable to infer the effect of post-school agricultural education compared to no formal agricultural education. It would be expected that, given the technical nature of PATs, those with agricultural education would be more likely to adopt these technologies compared to those without agricultural education. Similarly, for income specialisation, which was a categorical response, this was reduced to a binary variable reflecting specialisation of income generated from a particular enterprise.

## *3. Results*

Table 4 shows the marginal effects of both the multinomial logistic regression and the binomial logistic regression. What emerges are similar patterns of significance for MG Only and VRNT bundle adoption compared to non-adoption, but differences between MG Only and VRNT bundle adoption.

**Table 4. Estimates for multinomial and binomial random intercept models (marginal effects)**

Size of farm is significant and marginally positive compared to non-adoption. As utilised agricultural area expands there is a slightly higher propensity for farmers to adopt MG Only or VRNT bundles compared to non-adoption. The effect is similar to the positive effect of land area found by a number of authors (Fernandez-Cornejo *et al*., 2001; Pierpaoli *et al*., 2013; Castle *et al*., 2016; Schimmelpfennig, 2016). Notably for the binomial model this is not significant, indicating that size may be a threshold indicator between adoption and non-adoption but is not characteristic of adopting VRNT bundles above MG Only.

Age of farmer is significant for adoption of MG Only technologies, indicating that as farmers get older they are less likely to adopt these technologies, with a greater probability that they will not adopt when farmers are over 65 years of age. This matches previous findings on age and highlights the short planning horizon of older farming as a barrier to invest in PATs (Lambert *et al*., 2015; Miller *et al*., 2017). Specialised agricultural education was developed as a predictor for uptake. This variable was used to infer a higher level of knowledge towards agricultural decision-making to capture the shift to an information intensive based technology. However, this did not prove significant. In addition we find no significant impact on land ownership determining adoption of either technology. This has been seldom explored within past studies, although Paustian and Theuvsen (2016) found some significant differences on PAT adoption with farmers who leased larger areas of land. However, they did not specifically examine ownership status as a predictor of uptake.

Household income is also an important factor in determining adoption of PATs as it reflects the economic barrier to non-adopters. Specifically, higher levels of income creates the capacity to accommodate longer payback periods as this infers the availability of cash reserves to handle longer time periods for paying back the technology. The effect of income is positive and the magnitude is larger for those adopting MG only compared to VRNT technologies. This result agrees with literature on PATs, indicating that adoption has high entry costs and higher income farmers are more likely to adopt them (Diederen *et al*., 2003; Schimmelpfennig, 2016; Miller *et al*., 2017). Again, income did not determine adoption of VRNT bundles compared to MG Only uptake within the binomial regression, which may be reflective, like size of holding, of a threshold effect needed to adopt PATs rather than discriminate between PATs.

Specialisation of income from wheat or potatoes is not a factor for adoption. Nevertheless, the ratio of arable land to total land has high probabilities of adoption for both MG only and VRNT bundles against non-adoption. This can also indicate economies of scale and the reducing of costs on a per unit basis enables a return to investment on PATs.

If a farmer is a member of a co-operative then there is some observed positive effect on uptake of MG only technology. Co-operatives and machinery rings do not as a whole provide support services for precision agriculture, e.g. data analysis, however they can serve as a proxy for information transfer between farmers (Rogers, 2003; Larson *et al*., 2008; Robertson *et al*., 2012; Lambert *et al*., 2015; Dimos *et al*., 2017). This has no effect on adoption of a VRNT bundle, perhaps indicating that this latter technology is more likely to be purchased within the farm rather than as a group asset to be shared amongst farmers.

Attitudinal factors have some effect. If the farmer perceives that PATs will provide an acceptable payback they are more likely to adopt machine guidance PATs compared to those who do not agree with this statement. Walton *et al.* (2008) used a fairly simple indicator of expected profitability but did not find a significant relationship. Hence, our attitudinal variable may capture a longer term view of returns to investment. Consequently, this attitudinal position offers some indication of potential for uptake of machine guidance. In addition, the level of current adoption of PATS (not including MG or VRNT) is used as a proxy for innovative behaviour and we find that if farmers have other PATS on the farm they are more likely to adopt both technologies. This agrees with a number of studies that show the effect of higher levels of technology on the farm which dictates PAT adoption (Isgin *et al*., 2008; Paxton *et al*., 2011; Castle *et al*., 2016). As would be expected a VRNT bundle is a more advanced technology, which may explain the greater influence of this variable. The technologies, which are similar to MG and VRNT, can also be understood as an indication that farmers also have access to ancillary capacity for data collection, processing and decision making (Miller *et al*., 2017).

The statement on perceived profitability, '*I am too uncertain of the effects of PAT to invest in it'* is negative and significant for those who adopt VRNT bundles, compared to MG only. This may be indicative of the differences in the type of technology adopted, where one is embodied knowledge and the other information intensive. Specifically, the perception of the PAT having an effect is more explicitly embodied in VRNT which encourages more active engagement compared to MG, which is passive, and therefore the perceived effect of adoption is much lower. In addition, it may be attached to the income effect, where larger enterprises who are more likely to adopt VRNT would also be more likely to adopt systematic approaches towards calculating the return to investment of different technologies (Martin *et al*., 2017; Shockley *et al*., 2017). However, calculating return on investment for PATs is complicated by the heterogeneity of individual farm land (Robertson *et al.*, 2007; Montalvo, 2008) and it may be that the large income of VRNT adopters simply creates a buffer for absorption of losses at the whole farm scale and therefore may simply generate optimism towards payoffs from this technology.

Only the adopters were queried on external influences on adoption, and there was a significant and positive effect for the use of an advisor. Robertson *et al.* (2012) and Larson *et al.* (2008) also identified advisors as a source which farmers respond to and lead to greater likelihood of adoption of these technologies. However, whilst advisors provide a source of information which influences their decision to adopt VRNT there seemed to be no effect of farmer-to-farmer networks on uptake of VRNT bundles compared to MG Only. A great deal of literature has focused on the effect of peer group influences (see Rogers, 2003) though little has been applied within the arena of PAT adoption. It may be that the economic significance of the decision, in terms of the technology applied, may dissuade the focus on farmer to farmer networks and rely on technical support from advisors but this needs to be tested further within the literature.

## 4. Discussion and Conclusions

A large scale survey of cross-regional attitudes and perceptions towards uptake of PATs provides a detailed understanding of the commonality of barriers between adopters and non-adopters across countries and, consequently, identifies potential public interventions which encourage uptake.

The main barrier found within the literature seems to be the high cost of entry and this is further confirmed here as bigger farms tend to be more likely to adopt PATs, compared to smaller farms, but also very large farms are more likely to adopt an information intensive PAT package. The operation of variable rate technology is intrinsically different to machine guidance, which is passively operated, and a VRNT bundle provides opportunities for greater interaction with, and a more codified approach towards, the heterogeneity of a farm's terrain. This is in contrast to the embedded knowledge of the farmer towards their land and raises issues on how PATs may be challenging farmer identities towards farming and their farming knowledge itself (Tsouvalis *et al.*, 2000; Burton *et al.*, 2004).

Uptake of VRNT bundles may also infer a particular attitudinal perspective or explicit profit driven approach to farming that dictates uptake. This is further confirmed here as those farmers with less uncertainty towards the economic return of VRNTs are more likely to invest in them. Given that PATs are generally high cost and conditioned to work across heterogeneous soils, there would be more expectation of an economic return from this investment. Numerous studies have found, if operated optimally, that adoption of PATS is positive for economic goals (e.g. Godwin *et al.*, 2003; Batte and Ehsani, 2006). This 'economic certainty' may also be supported by the economic size of the farm to leverage risk taking.

Arguably, the present income support payments under the Common Agricultural Policy, although now mostly, and technically at least, decoupled from production, provides a hedge for risk taking and therefore indirectly does support adoption of newer technologies, of which PATs will be the primary target. Consequently, the reduction in CAP support which has been observed over the last two decades, and indications that this will reduce further (European Commission, 2017), may lead to a bi-modal direction of travel for farming communities with regard to PATs. Effectively, larger profit motivated farmers will be the primary users of PATs, whereas the remainder will be non or low-level adopters. The reduction of subsidy, which could negate some of the risk to investment, may further remove the incentive for this low-level adoption community to participate and therefore create further inequalities in the farming sector. Hence, public policy intervention may induce innovation within the farming industry by supporting data solutions that are required for running bundles of PATs in rural regions, with the free provision of geospatial mapping data at fine resolutions for European countries. This may provide a useful route for increasing awareness, as large scale investment within a country's infrastructure may raise the expectation of a positive economic return.

Information intensive technologies also require a further investment in learning and there may be a gap between industry support and the user ability to operate machines optimally. Given the attitudinal and resource constraints outlined above, support for learning may offer a stronger argument for the role of the public sector in PAT uptake. It emerged that around 50% of respondents in the survey ranked some form of training as a potential incentive to encourage uptake (Figure 2). However, from the respondents' perspective the most popular stated incentives would be financial incentives or more certainty that the technology would improve biophysical or economic performance. The lack of certainty may also echo the previous findings that farmers cannot assess the rate of return to investment, or do not trust experimental farm studies given potential heterogeneity of individual farms. Nevertheless, the dissemination of knowledge around the effects of PATs, operating within different regions and contexts would seem to be a means to negate this uncertainty and potentially support a decision to purchase the technology.

**Figure 3. Incentives for encouraging uptake, ranked by response**

The planning transition between non-adoption and adoption is complicated by the influence of machinery suppliers on determining the purchase decision and negation of skepticism towards the perceived results from adoption. Promotion of PATs through Government support may, therefore, be through demonstration of actual benefits and support for training. Whilst there is some EU support for modernization of machinery, there is no regulatory push to adopt PATs and this is purely a commercial decision. However, whilst the prevailing feeling towards precision farming in public policy circles is favorable, it is questionable whether the public sector really has a role in supporting adoption of PATs at all. The development of PATs is an example where commercialization by industry will recoup private returns (Barnes, 2001). Consequently, the focus of policy incentives may be more acceptable, given resource constraints, when targeted towards engagement in knowledge building and demonstration of PATs to encourage efficient use and uptake.

The main argument for government intervention relies on the ability of PATs to improve resource use efficiency at such a level that public goods will be protected and preserved whilst increasing the supply of food needed for a growing population. However, there is a paucity of studies to indicate a compelling link between the ability of PATs to both reduce environmental impacts and increase economic benefits. Studies tend to argue that there are great sensitivities which limit obtaining consistent results when applied in practical field situations (Wheelen and McBratney, 2000; Brennan *et al*., 2007).

This highlights a cultural challenge embedded in PATs, as, whilst the ethos of precision agriculture is to take a more targeted approach to farming, PATs represent a distinctively technological approach to agriculture which may not match the perspectives of low-input, extensive or organic producers. This questions the public support for precision agriculture within farming generally as, unlike, other holistic management approaches, such as integrated farm management, precision agriculture could lead to more input usage through greater intensification. This may present an example of a 'rebound' effect where increased resource use efficiency leads to unintended resource depletion as systems increase in scale (Alcott, 2005) The further alignment of these PATS to the contested term ‘sustainable intensification’ (Godfrey et al., 2010; Gebbers and Adamchuck, 2010) may also create barriers to small-scale, or organic and low-input farmers who could benefit from adoption of PATs but are deterred by this technological ethos (Hanspach *et al*., 2013; McDonagh, 2015; Barnes *et al*., 2016).

It is less clear that conventional socio-economic characteristics determine uptake. Whereas past literature does find operator age and education to be important (Tey and Brindal, 2012) a recent study in Germany could find no significant effect of these factors (Paustian and Theuvsen, 2016). We find that, on the whole, younger farmers are more likely to adopt the technology. This potentially links to the knowledge requirements to optimally operate information intensive technologies, and age is also perhaps reflective of literacy in operation of more computationally intense machinery. For other categories of adoption and non-adoption we could find no effect of educational status. Within the literature on technology adoption education does generate mixed results. This is perhaps also reflective of Huffman’s (2001) argument that education variables tend to lead to biased interpretations of intellectual achievement which, in terms of precision agriculture, should extend to skills accommodating data management and interpretation, and knowledge of more complex operating systems. Potentially this calls for a more sophisticated latent variable approach to understanding uptake, where the farmer state of knowledge is inferred by a number of candidate variables of which only aspect is educational attainment (e.g. Toma *et al*., 2018).

Furthermore, it may be the case that farmers who positively perceive that PATs would payback, which leads to more uptake, may be an artifact, at least for some farmers, of post-purchase rationalization bias (Cohen and Goldberg, 1970). Effectively, given the high level of investment required, farmers are seeking self-assurance or legitimacy to validate their decisions and may view outcomes as more positive, even though they haven’t experienced them yet. This phenomenon could be explained through “cognitive dissonance” theory (Festinger, 1957), which states that contradictory beliefs or ideas (e.g. the decision to adopt a PAT while considering that it may not be profitable) cannot be held at the same time without creating a tension and conflict in the individual. The results presented here indicate that the decision to progress from the adoption of an embodied knowledge technology (i.e. MG) to an information intensive technology (i.e. VRNT) is significantly influenced by farm advisors. This might be linked with the fact that when venturing into more expensive and data demanding technologies, farmers seek support from experts to validate their decisions (Tsouvalis *et al.*, 2000; Ingram, 2008).

Some of this may be evidenced by the polarity of opinion expressed by adopters towards machine guidance which were balanced in equal proportions of agreement and disagreement towards whether the technology would payback. This may infer that there are further groups operating within these adoption states based on outlook and experience of the PAT and perhaps further work can explore ways to cluster farmers beyond the purely technology adoption states presented here (see for example Barnes *et al.*, 2011; Islam *et al.*, 2013)

Finally, whilst we have quantified the main drivers of uptake it is probably the case that softer factors also determine adoption and this may make regional differences more explicit, such as farmer to farmer networks and inequality of commercial interests. Moreover, the opportunities for demonstrating the technology, through researchers and trade fairs may provide an important aspect of the determining uptake of these technologies. The literature on PATs is lacking in any detailed qualitative studies of uptake and further work should probably examine the role of these cultural factors of farming and how sophisticated technologies, such as PAT, may create barriers to future adoption.

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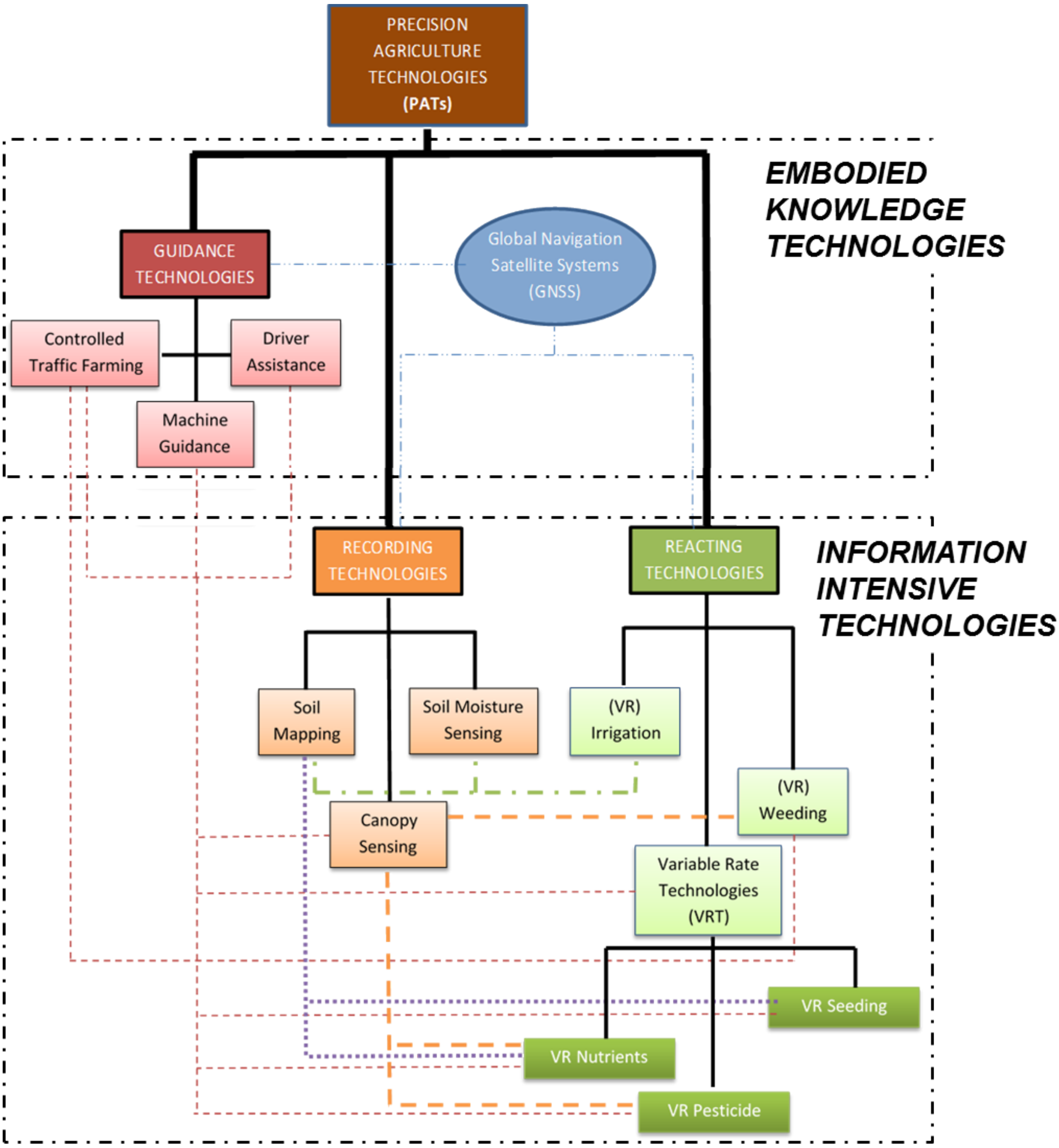
**Figure 1. Hierarchy of Precision Agricultural technologies**




Source: modified from Balafoutis *et al*. ( 2017)

**Figure 2. Hypothesised Relationships between the variables and the two adoption states**

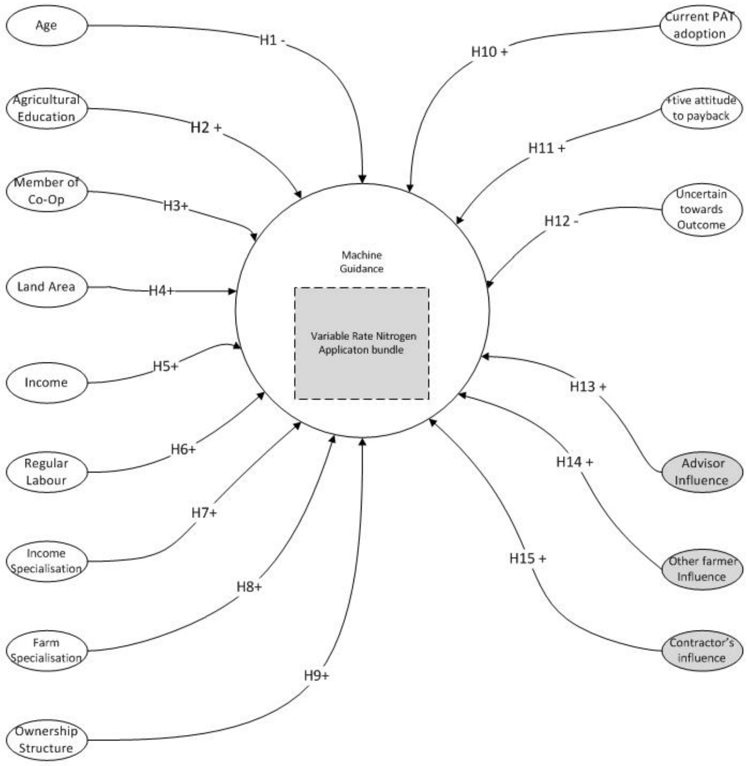


**Figure 3. Incentives for encouraging uptake, ranked by response**

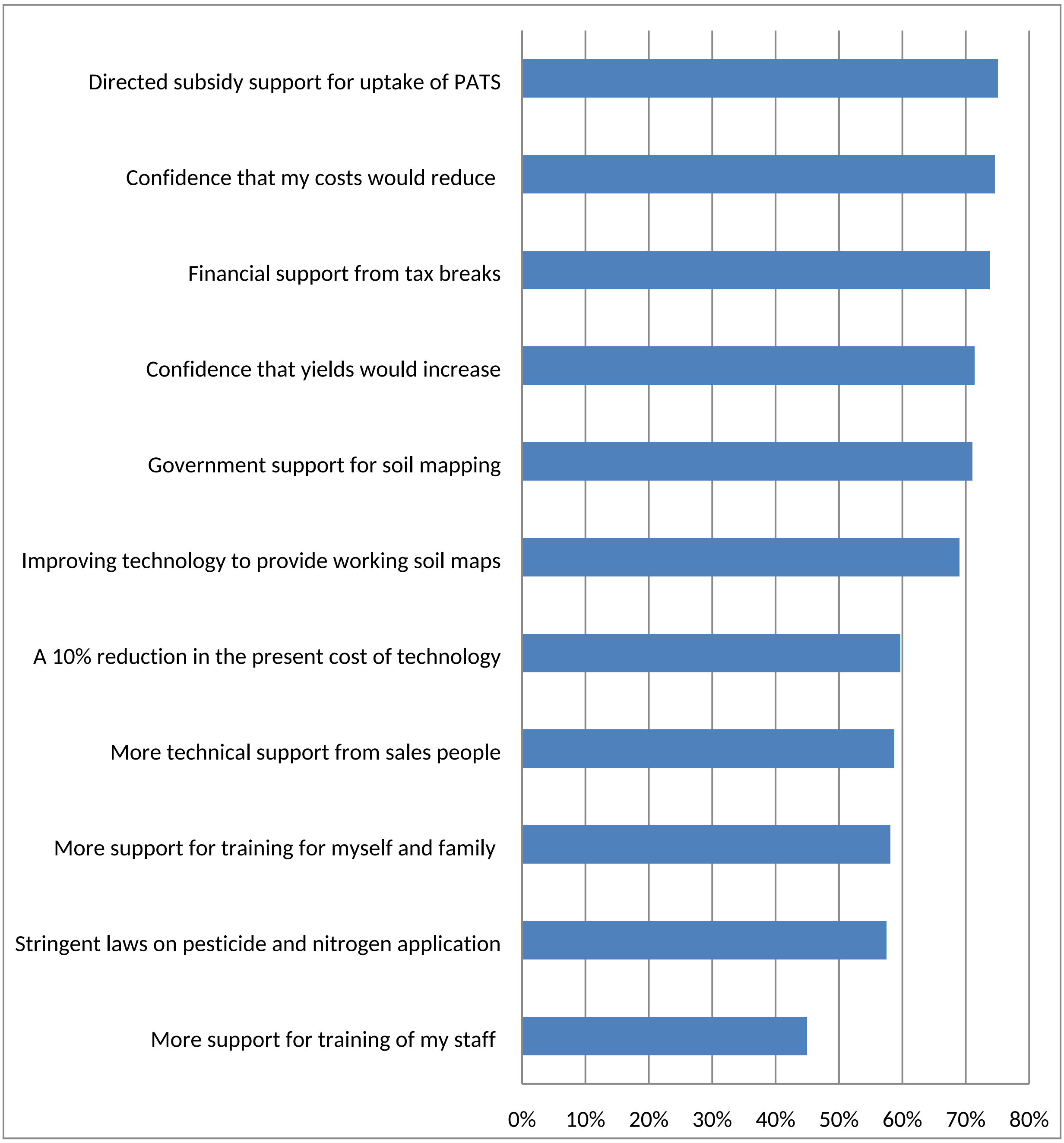


**Table 1: Distribution of contact methods by region, number of individuals**

| | Interview Method | n | Farmers contacted through: | n |
|---|---|---|---|---|
| Greece (n=200) | Face to face | 200 | Machinery dealers | 183 |
| | Telephone | 0 | Personal contacts | 17 |
| Belgium (n=196) | Face to face | 196 | Personal contacts | 196 |
| | Telephone | 0 | | |
| Netherlands (n=176) | Face to face | 175 | Trade fair | 142 |
| | Telephone | 1 | Personal contacts | 34 |
| Germany (n=195) | Face to face | 0 | | |
| | Telephone | 195 | Agricultural Database | 195 |
| UK (n=204) | Face to face | 134 | Trade fair | 28 |
| | Telephone | 70 | Agricultural Database | 176 |

**Table 2. Descriptive statistics of main land use and labour categories from the survey by region, mean**

| | | Winter Wheat, ha | Spring Wheat, ha | Ware Potatoes*, ha | Seed Potatoes, ha | Utilised Agricultural Area ha | Arable Area, ha | Full-Time Employees | Family Members | Part-Time & Seasonal Employees |
|---|---|---|---|---|---|---|---|---|---|---|
| Belgium | Non-Adoption (n=150) | 5.2 *(7.0)* | 0 *(0.02)* | 4.8*(8.5)* | 0.0 *(0.0)* | 35.7 *(24.4)* | 25.4 *(18.5)* | 0.0 *(0.4)* | 1.4*(0.9)* | 0.8*(1.1)* |
| | MG Only (n=42) | 10.6*(10.2)* | 0.1 *(0.8)* | 13.7 *(15.0)* | 3.1 *(15.25)* | 70.6 *(38.1)* | 57.1 *(37.5)* | 0.1 *(0.2)* | 1.6*(0.8)* | 1.2*(1.9)* |
| | VRNT Bundle (n=4) | 7.3 *(3.8)* | 0*(0.0)* | 13.3*(15.9)* | 0.3 *(0.5)* | 49.3 *(24.4)* | 40*(32.3)* | 0*(0.0)* | 1.8*(0.9)* | 2.3*(2.6)* |
| Greece | Non-Adoption (n=102) | 33.3 *(32.0)* | 14.3 *(21.9)* | 12.5* *(15.4)* | | 67.8 *(54.9)* | 67.4*(54.8)* | 2.2*(1.2)* | 1.8*(0.73)* | 2.1*(1.8)* |
| | MG Only (n=71) | 25*(27.2)* | 36.1 *(36.2)* | 14.6* *(23.6)* | | 82.1*(35.9)* | 82*(36.1)* | 2.7*(1.1)* | 1.9*(0.7)* | 2.3*(1.3)* |
| | VRNT Bundle (n=27) | 47.8*(33.9)* | 43.3*(42.1)* | 55.7* *(52.1)* | | 153.4*(43.2)* | 153.4*(43.2)* | 4.2*(1.3)* | 2.2*(0.9)* | 3.6*(2.0)* |
| UK | Non-Adoption (n=47) | 33.7*(36.8)* | 11.7*(14.9)* | 4.3*(10.5)* | 5.5*(10.1)* | 228.3*(210.6)* | 166*(119.8)* | 1.4*(1.4)* | 1.4*(1.1)* | 5.1*(18.3)* |
| | MG Only (n=61) | 54.3*(50.1)* | 30.7*(36.7)* | 7.6*(13.6)* | 7.3*(13.8)* | 251.8*(130.9)* | 209.8*(111.9)* | 1.8*(1.9)* | 1.5*(1.3)* | 3.8*(10.2)* |
| | VRNT Bundle (n=96) | 70.5*(68.8)* | 35.7*(42.2)* | 5.4*(10.8)* | 4.2*(9.5)* | 352.4*(426.3)* | 252.8*(163.6)* | 2.0 *(2.2)* | 1.2*(1.1)* | 2.9*(6.6)* |
| Germany | Non-Adoption (n=79) | 25.3*(28.7)* | 0.4*(1.8)* | 3.7 *(9.9)* | 0.1*(0.7)* | 141.7*(187.3)* | 106.1*(127.6)* | 1.0*(2.5)* | 1.1*(0.9)* | 0.9*(1.5)* |
| | MG Only (n=66) | 147.5 *(244)* | 2.1 *(12.6)* | 16.6 *(56.6)* | 1.4*(5.7)* | 639.9 *(984.1)* | 537.5*(821.4)* | 6*(12.1)* | 1.2*(1.2)* | 3.4*(7.4)* |
| | VRNT Bundle (n=50) | 284.6*(352.9)* | 1.2*(7.2)* | 18.5*(46.0)* | 1.6*(7.6)* | 1046.1 *(1122.0)* | 847 *(883.7)* | 10.3*(13.1)* | 0.9*(1.1)* | 2.3*(3.9)* |
| Netherlands | Non-Adoption (n=50) | 11.6*(9.5)* | 0.8*(2.8)* | 11.1*(13.5)* | 4.7*(15.4)* | 52.8*(42.0)* | 48.9*(41.9)* | 0.5*(1.5)* | 1.1*(1.1)* | 1.1*(2.0)* |
| | MG Only (n=84) | 33.3*(58.2)* | 1.1*(4.9)* | 61.5*(278.7)* | 6.6*(15.2)* | 156.6*(289.9)* | 152.2*(391.1)* | 0.9*(1.2)* | 1.4*(1.2)* | 2.1*(3.8)* |
| | VRNT Bundle (n=42) | 64.5*(101.2)* | 5.6*(13.7)* | 70.4*(111.0)* | 7.3*(11.7)* | 229.2*(303.3)* | 211.1*(238.58)* | 1.8*(2.9)* | 1.4*(0.9)* | 1.2*(1.2)* |

*For Greece this refers to Cotton area, Ha;

MG Only: respondents who only adopted machine guidance; VRNT Bundle: those respondents who adopted both machine guidance and variable rate nitrogen management

**Table 3: Variables used within the empirical model**

| Variable | Type | Description |
|---|---|---|
| **SOCIOECONOMIC CHARACTERISTICS** | | |
| Age | Categorical | 0:<45; 1:45-65; 2:>65 |
| Agricultural Education | Binary | 0: No formal agricultural education ; 1: post-school college or higher education in an agricultural subject. |
| Member of a marketing co-op | Binary | 0:Not a member; 1:Marketing Co-op |
| Member of machinery co-op | Binary | 0:Not a member; 1: Machinery Collective; |
| **STRUCTURAL AND FINANCIAL CHARACTERISTICS** | | |
| Size | Continuous | Sum of total area in hectares |
| Income Class | Categorical | 0:<100k; 1:100-300k; 2:+300K |
| Regular Labour | Continuous | Sum of regular labour in total staff numbers |
| Income Specialisation | Binary | 0: <60% of income from specific crop<br>1: > 60% of income from specific crop |
| Farm Specialisation | Continuous | Ratio of arable land to total land area from 0 to 1, where 0 is no arable land to total land area and 1 is arable land covers total land area |
| **CURRENT TECHNOLOGICAL ADOPTION** | | |
| Level of current technological adoption* | Continuous | A scale from 0 to 4 which indicates the amount of other PATs currently on farm where 0= no other PATS and 4=4 other PATs. |
| **ATTITUDINAL CHARACTERISTICS** | | |
| Positive towards payback | Binary | Attitudinal statement where 0 = Not positive towards payback of PATS;<br>1= Positive towards payback statement of PATs |
| Uncertain towards outcomes | Binary | 0: Less uncertain; 1: More uncertain towards outcomes |
| **INFORMATIONAL CHARACTERISTICS** | | |
| Advisor± | Binary | 0: Not an influence; 1: Advisors as influences of adoption |
| Farmers± | Binary | 0: Not an influence; 1: Other farmers as influences on adoption |
| Contractors± | Binary | 0: Not an influence; 1: Contractors as influences on adoption |
| **INSTITUTIONAL CHARACTERISTICS** | | |
| Management Structure | Binary | 0:Owner; 1: Tenant; 2: Other |

*± Only adopters were asked this question and therefore could only be used to compare different classes of adoption.*

** This index did not include MG and VRNT PATs to avoid multicollinearity issues.*

**Table 4. Estimates for multinomial and binomial random intercept models (marginal effects)**

| | Multinomial Logit | | | | | | Binomial Logit | | |
|---|---|---|---|---|---|---|---|---|---|
| | MG Only | | | VRNT Bundle | | | | | |
| | *marginal effect* | | *se* | *marginal effect* | | *se* | *marginal effect* | | *se* |
| *Age (reference class: <45)* | | | | | | | | | |
| 45-65 | -0.112 | ** | *0.036* | -0.031 | | *0.034* | 0.047 | | *0.044* |
| Over 65 | -0.256 | *** | *0.047* | -0.082 | | *0.046* | 0.089 | | *0.087* |
| Above school agricultural education | 0.005 | | *0.038* | 0.041 | | *0.035* | 0.081 | | *0.046* |
| *Management. Reference class: owner-occupied* | | | | | | | | | |
| Tenanted | -0.073 | | *0.069* | -0.010 | | *0.056* | 0.049 | | *0.096* |
| Other | -0.019 | | *0.048* | -0.057 | | *0.039* | 0.015 | | *0.058* |
| Size | 0.001 | *** | *0.000* | 0.001 | *** | *0.000* | 0.0001 | | *0.000* |
| Regular Labour Employed | -0.003 | | *0.013* | 0.004 | | *0.010* | 0.001 | | *0.006* |
| *Specialisation (reference class: less than 60% income from wheat)* | | | | | | | | | |
| Potato Income | 0.004 | | *0.049* | -0.011 | | *0.044* | -0.070 | | *0.057* |
| Wheat income | 0.033 | | *0.039* | -0.054 | | *0.036* | -0.065 | | *0.051* |
| Ratio of arable land to total land | 0.365 | *** | *0.097* | 0.361 | *** | *0.100* | -0.046 | | *0.129* |
| *Income class (reference class: less than 100,000 euros)* | | | | | | | | | |
| 100,000-300,000 Euros | 0.075 | | *0.040* | 0.039 | | *0.047* | 0.004 | | *0.051* |
| >300,000 Euros | 0.125 | * | *0.054* | 0.076 | * | *0.037* | 0.017 | | *0.055* |
| Level of current adoption of PATs | 0.048 | ** | *0.016* | 0.066 | *** | *0.012* | 0.061 | *** | *0.017* |
| Membership of machinery collective | 0.090 | | *0.048* | 0.035 | | *0.045* | -0.047 | | *0.059* |
| Membership of marketing co-operative | 0.149 | ** | *0.051* | 0.072 | | *0.041* | -0.066 | | *0.053* |
| Positive towards payback | 0.111 | ** | *0.033* | -0.016 | | *0.029* | -0.050 | | *0.055* |
| More uncertain towards outcomes | -0.019 | | *0.038* | -0.086 | ** | *0.032* | -0.140 | ** | *0.042* |
| Influenced to adopt by advisors | | | | | | | 0.091 | * | *0.035* |
| Influenced to adopt by other farmers | | | | | | | 0.023 | | *0.043* |
| Influence to adopt by contractors | | | | | | | -0.025 | | *0.035* |
| Log-likelihood | -507.6 | | | | | | -321.6 | | |
| Number of Observations | 971 | | | | | | 543 | | |

*Standard errors in italics * p<.05 ** p<.01 *** p<.001*