Understanding UK Farmers' Brexit Voting Decision: a Behavioural Approach

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Abstract: *In spite of the potential negative effects that Brexit could bring to the United Kingdom (UK), the majority of the electorate voted to leave the European Union (EU). As a result of this paradoxical choice, a number of studies have been developed to understand the factors that triggered this voting decision. Most of them take into account factors related to immigration from East Europe, national identity, and sovereignty recovering, among others. However, these factors do not seem to reflect the reasons behind farmers' Brexit voting choice. Using a behavioural approach based on the theory of planned behaviour, the aim of the study was to contribute to the body of literature by undertaking an indicative study of UK farmers' Brexit voting decisions. The study found that for the sample group, voting choice was strongly influenced by farmers' perceptions about EU legislation, their attitudes towards the EU, their perceived capacity to control factors that impact on the farm performance, their sense of self and their notions of autonomy within the confines of prescriptive agricultural policy and the influence of their social relationships.*

Keywords: farmer, decision making, voting, preference, Brexit

Highlights:

- **Geographic location influenced voting preference.**
- **Type of farm enterprise and farm size influence voting preference.**
- **Attitude towards the EU had the highest predictive power of voting intention.**
- **Farmers with greater social relationships more likely to vote to remain in EU.**

1. Introduction

On June 23, 2016, a referendum held in the UK marked a turning point in the history of Europe in general, and the country in particular, as a majority voted to leave the EU in what is referred to as Brexit (Becker, 2016). Economists and policymakers at that time manifested significant concern about the possible negative impacts of this decision on British voters. The "Leave" versus "Remain" campaigns used a variety of narratives to engage voters and some have suggested there was a real juxtaposition between a discourse based on feelings rather than an objective discourse based on facts but the real element of voter engagement was around trust (Forss and Magro, 2017). Indeed Forss and Magro (2017) argues that the facts presented in the Brexit campaign were in themselves not free from association with ideology or inferred meaning and thus were not seen as neutral information, but were contextualised by voters especially by those who felt "left behind" and did not trust "expert" policymakers.

The EU Referendum result saw a turnout of 72.2% from an electorate of 46.6 million people with 16,141,241 individuals voting remain and 17,419,742 individuals voting to leave (Electoral Commission, 2019). A further breakdown of voting preference by region has been compiled in Table 1.

Table 1 Results and turnout at the EU referendum (Adapted from The Electorial Commission, 2019).

Region	Leave (%)	Remain (%)
West Midlands	59.3	40.7
East Midlands	58.8	41.2
North Est	58.0	42.0
Yorkshire and the Humber	57.7	42.3
East	56.5	43.5
North West	53.7	46.3
South West	52.6	47.4
Wales	52.5	47.5
South East	51.8	48.2
Northern Ireland	44.2	55.8
London	40.1	59.9
Scotland	38.0	62.0
All regions	51.9	48.1

A number of studies were assessed the impact of a “leave outcome” concluding that Brexit would cause significant economic damage to the country. For example, Sampson (2017) predicted that Brexit will make the UK poorer because it will lead to new barriers to trade and migration, and a decrease in foreign investment that altogether could cost between 1 and 10 percent of per capita income. Likewise, Dhingra et al. (2016) predicted an annual cost of £850 (£4,200 in the long run) per capita with a ‘soft Brexit’ as a consequence of an increase in non-tariff barriers and the exclusion from further EU market integration, and an annual cost of £1,700 (£6,400 in the long run) per capita in the ‘hard Brexit’ scenario as a result of additional non-tariff barriers as well as the introduction of bilateral trade tariffs. The negative impact of Brexit on the UK has also been predicted by a number of further studies (see for example Brakman et al. 2018; Dhingra et al. 2018; Kierzenkowski et al. 2016; Portes and Forte, 2017).

In spite of the possible negative effects of Brexit on the country, there was a majority of UK voters who voted in favour of leaving the EU. This was explicitly noted by Los et al. (2017) who point out that the regions that voted for Brexit in large numbers potentially have the most to lose from Brexit itself (Table 1). According to Garretsen et al. (2018), this paradoxical outcome can be explained by the fact the main driver for the voting decision was not economic self-interest, but instead a range of attitudes, feelings and perceptions. In this context, it is argued that negative attitudes toward immigration since the enlargement of the EU in 2004, as well as the perceived loss of economic sovereignty, national identities and fiscal resources for being an EU member are key factors behind the outcome of the referendum (Arnorsson and Zoega, 2018; Manners, 2018; Becker et al. 2017; Clarke et al. 2017; O’Reilly et al. 2016). Colantone and Stanig (2018) consider those communities that perceive themselves to be or are perceived by others to be the “losers in trade globalisation.” These are communities that have had to adjust most to the internationalisation of commerce and the inequity in gains derived from globalisation activities and as a result have negative feelings towards free market policies and instead favour protectionism. Indeed they argue that "individuals living in regions that receive stronger import shocks [i.e. the negative aspects of trade globalisation in terms of job losses and austere working and social conditions] are more inclined to vote for parties that are nationalist and isolationist." (Colantone and Stanig, 2018, p. 949).

In relation to these attitudes, feelings and perceptions, several studies have found that fear of immigration and multiculturalism were more pronounced amongst voters who were in a more vulnerable position in terms of labour market, poverty, lower levels of education, and also voters associated with demographics such as an older age, white ethnicity, collective narcissism (a belief in national greatness), adverse health, and low life satisfaction (see for example Alabrese et al. 2019; Becker et al. 2017; Golec de Zavala et al. 2017; Henderson et al. 2017; Liberini et al., 2017; Hobolt, 2016). In considering these factors, Arnorsson and Zoega (2018) argue that immigrants as neighbours were probably seen as dangers posed to society and older individuals may be driven by nostalgia when remembering life outside the EU.

Other studies have added other considerations that contribute in explaining the results of the referendum. For example, Fetzer (2018) argues that the austerity induced welfare reforms adopted from 2010 by the Conservative-led coalition government are key drivers to understanding voting patterns for Brexit. On the other hand, Abrams and Travaglino (2018) point out that negative attitudes toward immigrants are amplified when political trust was low. Further, voters in the referendum living in their county of birth were more likely to support Leave in areas experiencing relative economic decline or an increase in migrant population (Lee et al. 2018). Garretsen et al. (2018) postulate that psychological openness (i.e. intellectual curiosity and preferences for other or new ideas and influences) is not only a relevant predictor of individual political preferences, but also can explain why UK counties with higher trade openness towards the EU predominantly voted in favour of Brexit, where people in these counties have on average lower scores on psychological openness.

While these arguments seem to give reasonable explanations for the outcome of the Referendum at the country level, it is difficult to consider the factors determined as key drivers of farmers' voting decision. Even if farmers had negative attitudes towards immigration, voting in favour of Brexit, especially for those who use migrant labour, could damage their competitiveness as a consequence of a decrease in the number of workers. As a result of the seasonal nature of labour demand and falling unemployment in the UK, a significant number of farm businesses, especially with high labour enterprises such as horticulture, depend on the permanent and seasonal EU labour force (Swales and Baker, 2016). Limiting access to this type of labour would bring detrimental effects on the horticultural and manufacturing sector, particularly because the industry has reported a current shortfall in workers putting at risk some high-value crops (McGuinness and Grimwood, 2017). Despite these potential negative effects, it has been reported that a proportion of farmers voted for the "Leave" option expecting that the more restrictive and bureaucratic aspects of the EU health and safety regulations would be eliminated (Olivas-Osuna et al. 2019).

The motivation for this research is to seek to determine what influenced reported voting decisions and whether they were influenced by specific factors such as farmers' perceptions of EU legislation, their attitudes towards the EU, their perceived ability to control factors that impact on the farm performance, and their sense of self and notions of autonomy within existing agricultural policy. The aim of this research is to contribute to the body of literature by studying farmers' Brexit voting decision from a behavioural lens based on the theory of planned behaviour. The paper is organised as follows. Section 1 provides context from existing literature and studies. Section 2 presents the theoretical framework adopted in this study. Section 3 describes the methodology employed, Section 4 results and analysis. The paper then explores and discusses the findings in Section 5 and Section 6 provides conclusions for the study.

2. Theoretical framework

Socio-psychological approaches to study farmers' decision making are widely used to identify farmers' intention to pursue a determined behaviour such as technology adoption, policy adoption, participation in cooperation, entrepreneurial behaviour, and rural immigration, among others (Nakagawa, 2018; Deng et al. 2016; May, 2012; Bergevoet et al. 2004). Most of these studies are based on the theory of planned behaviour (developed by Ajzen, 1985). According to this theory, intention is a good predictor of behaviour. Intention is determined by positive or negative beliefs that an individual has that can be considered as attitudes (i.e., positive or negative attitude towards a behaviour), subjective norms (i.e., the influence of important referent individuals or institutions when approving or disapproving a particular behaviour), and perceived behavioural control (i.e., an individual's conviction that he or she will successfully execute a behaviour leading to a particular outcome). In this framework, perceived behavioural control can influence both intention and actual behaviour because it is more likely that a behaviour will occur when the perceived behavioural control is greater (Bergeovet et al. 2003). The theory postulates that the balance of the beliefs related to attitudes, subjective control and perceived behavioural control are what determines a positive or negative intention towards a particular behaviour. The basic framework of the theory of planned behaviour is presented in Figure 1.

The theory of planned behaviour was used as the theoretical framework to explain farmers' Brexit decision following the methodology adopted by Deng et al. (2016). In this framework, actual voting choice made by the farmers originated from their intention to perform a given behaviour. In this paradigm, Brexit voting was considered the observed behaviour of the underlying intention of either leave or stay in the EU.

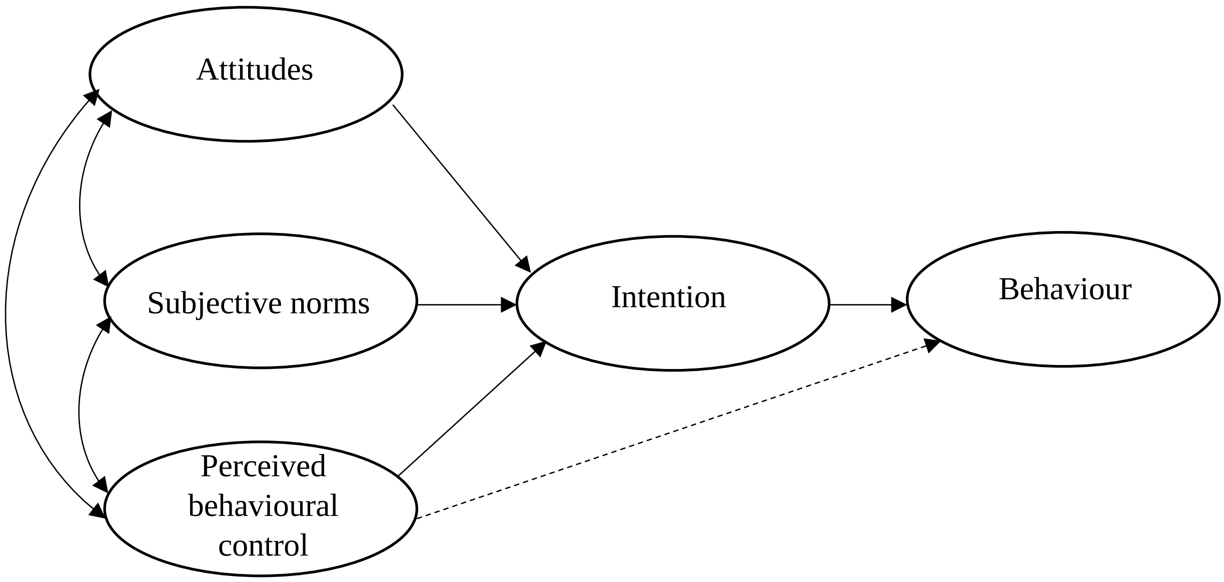

Figure 1. The theory of planned behaviour

Intention, in turn, is determined by farmers' attitudes towards the EU, perceived social pressure (i.e. subjective norms) from family members, neighbours and government regulations, and farmers' perceptions about their capacity to control the farming business.

This hypothetical model contains five latent variables or constructs: Attitudes towards the EU (AEU); subjective norms (SN); perceived behavioural control (PBC); Brexit voting intention (IN) and actual voting behaviour (AB). The testing of the relationships between these variables informed the design of a questionnaire that was used in the study. Each of the latent variables is reflected by two or more observable five-point Likert scale variables (from "strongly agree" to "strongly disagree") obtained from the questionnaire as answered by the sample of farmers in this study. Based on this theoretical framework, the following hypotheses were tested:

1. H1. AEU, SN and PBC as individual variables influence farmers' IN;
2. H2. The IN of farmers positively correlates with their AB;

3. H3. There are interactions between farmers' AEU, SN and PBC and their influence on IN; and
4. H4. PBC influences farmers' AB.

In order to test the suggested hypotheses from the theoretical framework in Figure 1, the PLS-SEM method was employed (see Section 3). This model is composed of two stages: (1) a measurement model analysis that shows the relationships between the latent variables and their indicators; and (2) a structural model analysis that describes the relationships between the latent variables. Both stages have to satisfy the indicators of reliability and validity. They are shown in Section 4.2. The methodology is now considered in more detail.

3. Material and methods

The literature review was undertaken to provide context for the empirical research and inform the question design. The rationales for the measures tested are explained as follows. In the case of the construct attitudes towards the EU (AEU), six statements were selected. Following the literature review, some of them capture key ideas in the debate on Brexit such as national identity, feelings against the EU, and the movement of people and goods (i.e. AEU_2, AEU_3 and AEU_5). Other statements related to economic perceptions of the farm and farming industry were included in the final questionnaire following comments by some farmers in a pilot consultation (i.e. AEU_1 and AEU_4). Finally, one statement was included to capture farmers' beliefs about possible negative effects of the EU on jobs and public services (AEU_6).

For the construct subjective norms (SN), seven statements were included. Some of these statements capture the influence of both the Brexit campaign and beliefs about available information on farmers' voting decision (i.e. SN_1, SN_2 and SN_5). Other statements capture the influence of local relationships between neighbours (i.e. SN_3 and SN_4). Finally, two statements were added to capture the point raised by Olivas-Osuna et al. (2019) that farmers who voted to leave made this choice expecting that the more restrictive and bureaucratic aspects of the EU health and safety regulations will be eliminated (i.e. SN_6 and SN_7).

For the construct perceived behavioural control (PBC), six statements were selected. Five of them capture beliefs about the capacity to control different aspects of farm business (i.e. PBC_1, PBC_2, PBC_3, PBC_4 and PBC_5), and one statement was including to account for farmers' beliefs about EU migrant labour force. The construct intention (IN) includes two statements associated with farmers' intention to vote before the referendum (i.e. IN_1 and IN_2). Finally, the construct actual behaviour (AB) includes one statement reflecting the actual voting choice made by the farmers (i.e. AB_1). The constructs and measurements in the theoretical model are outlined in Table 2.

Quantitative data for the constructs of the theoretical framework and their significant relationships was obtained from a self-administered on-line questionnaire based on 5-point Likert scale statements (1: Strongly disagree; 2: disagree; 3: indifferent; 4: agree; 5: strongly agree). Exemptions were the statement reflecting intention "when you heard about the EU referendum, what was your initial intention to leave?" (1=Leave; 2=undecided; 3=Remain) and the statement reflecting actual behaviour "how did you actually cast your vote in the EU referendum on 23rd June 2016?" (1= Leave; 2=I did not vote; 3=Remain) (see Appendix A). Profile questions were also included and the responses are summarised in Table 3. In relation to the statements "when you heard about the EU referendum, what was your initial intention to leave?" (i.e. IN_1) and "Before the referendum, I didn't think the UK should leave the EU" (i.e. IN_2), it is important to highlight the fact that they rely on participant recall about their initial intentions to leave. This is a potential limitation of this research because imperfect recall may introduce some biases in the data analysis. It is for this reason that the results have to be considered with caution.

Table 2. Constructs and measurements in the theoretical model.

Construct	Variables	Description of statements	Average response (Standard deviation in brackets)
AEU	AEU_1	Membership of the EU is a threat to a successful farming industry in the UK	2.95(1.15)
(Attitudes)	AEU_2	The free movement of goods and people between EU member states is a positive thing	2.49(1.17)
	AEU_3	I have always been opposed to UK membership of the EU	2.46(1.10)
	AEU_4	The economic outlook for farming would improve if we left the EU	3.09(1.15)
	AEU_5	Membership of the EU required surrendering our national identity	4.41(0.69)
	AEU_6	Membership of the EU causes a negative impact on jobs and public services	2.48(1.21)
SN	SN_1	The Brexit debate produced much propaganda and little reliable analysis	4.15(0.92)
(Subjective	SN_2	I considered the evidence on both sides of the Brexit debate before deciding how to vote	4.01(0.84)
norms)	SN_3	My social relationships influence my attitude to the EU	2.75(1.09)
	SN_4	Relationships between neighboring farmers could be damaged by disagreement over the EU	2.72(1.10)
	SN_5	It is important to be well informed before taking important decisions	2.93(1.25)
	SN_6	The amount of regulation farmers have to comply with would be reduced if leaving the EU	3.12(1.28)
	SN_7	Farmers would be free from restrictions on agrochemical use if leaving the EU	2.87(1.17)
PBC	PBC_1	Leaving the EU would make farming more profitable	3.12(1.17)
(Perceived	PBC_2	Leaving the EU would encourage farmers to invest in increasing food production	3.35(1.04)
behavioural	PBC_3	Leaving the EU would give farmers more power in the marketplace	3.25(1.20)
control)	PBC_4	Leaving the EU would decrease risk and uncertainty in the farming sector	2.39(1.20)
	PBC_5	Leaving the EU would give farmers more confidence in making farm business decisions	3.25(1.11)
	PBC_6	Leaving the EU would prevent farmers from employing EU migrant labour	2.12(1.15)
IN	IN_1	When you heard about the EU referendum, what was your initial intention to leave?	1.98(0.83)
(Intention)	IN_2	I do not think the UK should leave the EU	2.85(1.50)
AB (Actual behaviour)	AB_1	How did you actually cast your vote in the EU referendum on 23rd June 2016?	1.96(0.97)

The questionnaire was tested in a pilot study (n=25) and as described above the questions/statements where applicable were revised. The questionnaire was distributed to farmers via a snowball sampling technique. According to Salganik and Douglas (2004), this technique consists of selecting an initial small number of respondents referred to as seeds. After that, the seeds recruit others respondents from their friendship network to participate in the study. This process continues until the size of the sample selected for the investigation is reached. The snowball technique used in the current research follows a similar approach to that adopted by May et al. (2019) and Morais et al. (2017). That is, several seed farmers located in different relevant UK counties were selected with the purpose of covering a range of different geographical areas. The farmers who accepted to participate in the study were invited to complete an online survey. Using this approach, a sample of 523 farmers was obtained.

A limitation of the current investigation is that the non-probability based snowball technique does not guarantee representativeness and cannot inform about the precision degree of the results because it is not a random sample. This means that the study findings should be seen as indicative rather than representative. However, the decision was made to select heterogenous seed farmers across the UK in order to guarantee heterogeneity in the sample and to obtain a sufficient sample size to guarantee the statistical power of the model. In addition, because the variables are not normally distributed, the PLS-SEM method was employed as this is a non-parametric method that is suitable to work with this type of variables (see the discussion below). One potential limitation in the research design is confirmation bias and the potential for an individual to recall information in a way that confirms prior beliefs or values. The authors have noted this when they have reflected on the findings.

In the data analysis phase, descriptive analysis was undertaken of the demographic data to group the farmers by category and by variable in terms of percentage response (Table 3). The variables included the voting decision, gender, age, education, role on farm, farm type, farm size, geographic location and type of tenure. Using the data from the study, the Structural Equation Modelling (SEM) technique was then employed to identify any significant constructs and interactions between them. This method is defined by Hair et al. (2013) as a second generation multivariate method that aims to relate data and theory where prior knowledge is incorporated into an empirical analysis. The SEM technique combines observable variables and constructs by considering two models referred to as measurement and structural models. The measurement model specifies the relationships between the observable variables and constructs and their indicators. The structural model, on the other hand, describes potential relationships between the constructs. The SmartPLS software was used to run these models (Ringle et al., 2015). It is important to clarify that there exist two techniques of analysis of structural equation models that involve different characteristic and objectives: the models based on covariance structures referred to as covariance-based structural equation modelling (CB-SEM); and the partial least squares structural equation modelling (PLS-SEM).

The objective of the CB-SEM is to estimate the parameter values that best reproduce the variance-covariance matrix by means of maximum verisimilitude. This is done by imposing hypotheses of distribution of the data such as multivariate normality and independence of the data. Satisfying these hypotheses ensures consistency. For this purpose, it is necessary to have a large sample in relation to the number of variables included in the model.

On the other hand, the objective of the PLS-SEM models is to maximize the predictive power of the causal relationships of the model. This is achieved by minimizing the variance of the residuals of the model without imposing restrictions on the data distribution and requiring a relatively small number of observations (i.e. a minimum of 100 observations to ensure statistical power) with respect to the CB-SEM models (Martínez and Fierro, 2018).

In considering these differences, the current investigation adopted the PLS-SEM because this technique has to be selected when the investigation corresponds to either an exploratory study or the extension of an existing structural theory, no restrictions of normal distribution are imposed to the data, and the scale used for the items are ordinal (Marcoulides and Saunders, 2006; Henseler et al., 2016; Hair et al., 2013; Esposito Vinzi and Russolillo, 2010). In addition, this approach is more suitable to predict the dependent latent variables of the model by maximising the explained variance, R^2 (Rodríguez-Entrena, 2013).

The PLS approach was developed to reflect the theoretical and empirical conditions of social sciences and behaviour. The mathematical and statistical procedures are rigorous and robust. However, the mathematical model is flexible in the sense that it does not establish rigorous premises about data distribution, measurement scale, and sample size (Martínez and Fierro, 2018). The main objective of this methodology is to analyse casual-predictive consideration when problems are complex and when the theoretical knowledge may be limited

(Lévy and Varela, 2006). It is important to highlight the fact that the PLS technique can be used for explicative (confirmatory) investigation as well as for predictive (explanatory) investigation (Henseler et al., 2016; Hair et al., 2017; Rodriguez-Entrena et al., 2013).

According to Hair et al. (2017), the PLS-SEM has a number of advantages in comparison with other SEM techniques. First, this technique can employ small samples from 52 observations, although larger samples increase precision. In this regard, it is suggested a sample size of minimum 100 observations in order to obtain robust results. Our research satisfies this requirement because it involves a sample of 523 observations. Note that previous related research has also used small samples to understand farmers' behaviour (see May et al., 2019; Morais et al., 2017; Deng et al., 2016). Second, it is not necessary to assume normal distribution of the data. This is because the PLS-SEM is a non-parametric method and the recommended scale for this technique is Likert. Finally, each construct can be composed of one or more items and the relationships between constructs and their indicators can include reflective and/or formative variables (Martínez and Fierro, 2018; Roldan and Cepeda, 2016). The current investigation considers reflective items or variables. That is, items are a reflection of latent variables.

In considering these advantages, the PLS-SEM was adopted for two reasons. Firstly, the interactions between the latent factors or constructs of the theoretical framework based on the theory of planned behaviour are unknown. As a consequence, an exploration of possible relationships is required. Secondly, although the sample is not small (n = 523), the variables do not follow a normal distribution. This implies that the PLS-SEM is the most appropriate method for this study.

4. Results and analysis

This section reports the results obtained from the questionnaire. It starts describing the profile and main characteristics of the sample. After that, the results of PLS-SEM approach based on the data collected from the sample and the theoretical framework in Figure 1 are presented in three steps: firstly the results of the measurement model; secondly the results of the structural model; and finally the total effect results.

4.1. Sample profile

The main characteristics of the farmers in the sample and their Brexit voting choices are summarised in Table 3. During the literature review phase it was not possible to identify any source of data on farmer voting choice for Brexit so it cannot be included here to provide a comparison for the study. The descriptive statistics are organised as follows. The first column presents the dataset categorically, for example, 66% of the farmers in the category gender were male, and 34% were female. The other three columns inform about the reported voting choice made by farmers in each category. For example, 45% of females voted leave, 6% didn't vote, and 49% voted remain. Of the study population half stated they voted to leave, 45% stated they voted to remain and 5% stated they did not vote. Thus of those who voted in the survey population 52.6% voted to leave whilst 47.4% voted to remain. This is in line with to the national results of 51.9% voting to leave whilst 48.1% voting to remain (see Table 1).

Alabrese et al. (2019) identified attributes that were associated with voter decision on Brexit. These included employment status and they determined that those who were employed in the week before the vote were more likely to vote remain, but those with a permanent job as opposed to non-permanent were more likely to support leave. Further they highlight that those employed in manufacturing, construction and retail industries and self-employed individuals were more likely to support leave. As farmers mainly have self-employed status the research described herein would agree with Alabrese et al. (2019).

Table 4 shows the difference between the sample population and the proportion who voted to leave and the electoral result. The data shows some alignment e.g. in Wales, great diversity in terms of the reported farmers' vote and regional trend in favour of leave in Northern Ireland and Scotland and the reverse in the East Midlands and North East.

Table 3. Farmers' profile and reported Brexit voting choices

	Reported Brexit voting decision		
Category (percentage of farmers in each category in brackets)	**Leave (%)**	**I didn't vote (%)**	**Remain (%)**
Full sample	50	5	45
Age			
Under 34 (41%)	48	10	42
35-54 (35%)	50	2	48
55 or more (24%)	51	2	47
Gender			
Male (66%)	52	4	44
Female (34%)	45	6	49
Education			
GCSE or equivalent (24%)	60	6	34
A level or equivalent (42%)	51	6	43
Degree (23%)	42	5	53
Postgraduate (5%)	20	0	80
Other (6%)	56	3	41
Role on farm			
Holder, partner, director (38%)	51	1	48
Other member of farming family (16%)	46	6	48
Unwaged family farmer (17%)	46	10	44
Waged labour (16%)	55	11	34
Other (13%)	49	3	48
Farm type			
Cereals (13%)	42	9	49
Dairy (21%)	58	4	38
General cropping (6%)	47	3	50
Lowland grazing livestock (16%)	50	5	45
Upland grazing livestock (10%)	52	2	46
Mixed (28%)	46	5	49
Pigs/poultry (3%)	53	13	34
Other (3%)	50	0	50
Type of tenure			
Mainly owned (25%)	37	10	53

Mainly tenanted (6%)	41	4	55
Owner-occupied (56%)	53	4	43
Tenant (11%)	50	0	50
Other (2%)	80	0	20
Farm size (in hectares)			
0-150 (28%)	43	7	50
151-300 (26%)	48	4	48
301-450 (13%)	56	8	36
451 or more (33%)	53	3	44
Region			
East Midlands (8%)	42	2	56
East of England (8%)	55	10	35
North East (3%)	39	17	44
North West (4%)	62	0	38
Northern Ireland (12%)	53	10	37
Scotland (2%)	67	0	33
South East (10%)	44	6	50
South West (13%)	44	6	50
Wales (15%)	51	3	45
West Midlands (12%)	60	3	37
Yorkshire and Humberside (12%)	55	2	43

Table 4. Comparison of Leave vote in sample population against national vote

Region	Proportion of sample population who voted to leave (%)	Leave vote in Electoral Commission data (%) (Electoral Commission, 2019)	Difference (%)
West Midlands	61.9	59.3	2.6
East Midlands	43.3	58.8	-15.5
North East	46.7	58.0	-11.3
Yorkshire and the Humber	53.0	57.7	-4.7
East	61	56.5	4.5
North West	62	53.7	8.3
South West	46.8	52.6	-5.8
Wales	52.6	52.5	0.1
South East	46.8	51.8	-5.0
Northern Ireland	58.8	44.2	14.6
London	-	40.1	-
Scotland	67	38.0	29.0
All regions	52.6	51.9	0.7

The option leave was in general the dominant choice in all categories and also for the full sample. However, there are some exceptions. For example, remain was the dominant reported voting choice by female farmers. Hozić and True (2017) suggest this might be linked to the idea that de-regulation after departing from the EU could lead to the further removal of social supports, including some of the EU mandated maternity leave, and sources of public employment for women. However most of these women would be self-employed and as such have limited maternity rights so there may be other factors here that explain the differential. In relation to education, it was found that the majority of more educated farmers in the sample (i.e. farmers with either a degree or postgraduate qualification) reported that they voted remain. This finding is consistent with the voting trend associated with education status at the country level identified by other studies (see for example Alabrese et al. 2019; Becker et al. 2017; Henderson et al. 2017).

In relation to farm type, those who reported voting remain correspond to cereals, general cropping and mixed farms. Regarding type of tenure, this group correspond to mainly owned and mainly tenanted farming businesses. In the case of farm size, it is observed that the majority of farmers operating in small farms voted remain, but this choice is reversed as the size of the farms becomes larger. Finally, the results shows that the majority of farmers located in East Midlands, North East, South East and South West reported they voted in favour of remain suggesting that this option was the dominant in the east and south parts of the country in the case of the farming sector, which in part reflects the positioning of the national voting trends. We do not have explanations for these descriptive findings. However, some possible insights may be gained by using the behavioural model developed in this research and this is now considered.

4.2. Results from the PLS-SEM approach

This section reports the results obtained from the PLS-SEM analysis and they are presented in the three steps followed in the study: fitting results of the measurement model;

fitting results of the structural model; and total effect results. The discussion section provides analysis of meaning. Note that sociodemographic dummy variables were not included in the results because they were not significant (see Appendix B).

4.2. 1. Fitting results of the measurement model

The measurement model generated by the data describes how each construct is explained by the observable variables. The results presented in Figure 2 and Table 5 show good psychometric properties implying that the estimation of the constructs and the validity and reliability conditions are all satisfied. This is explained as follows.

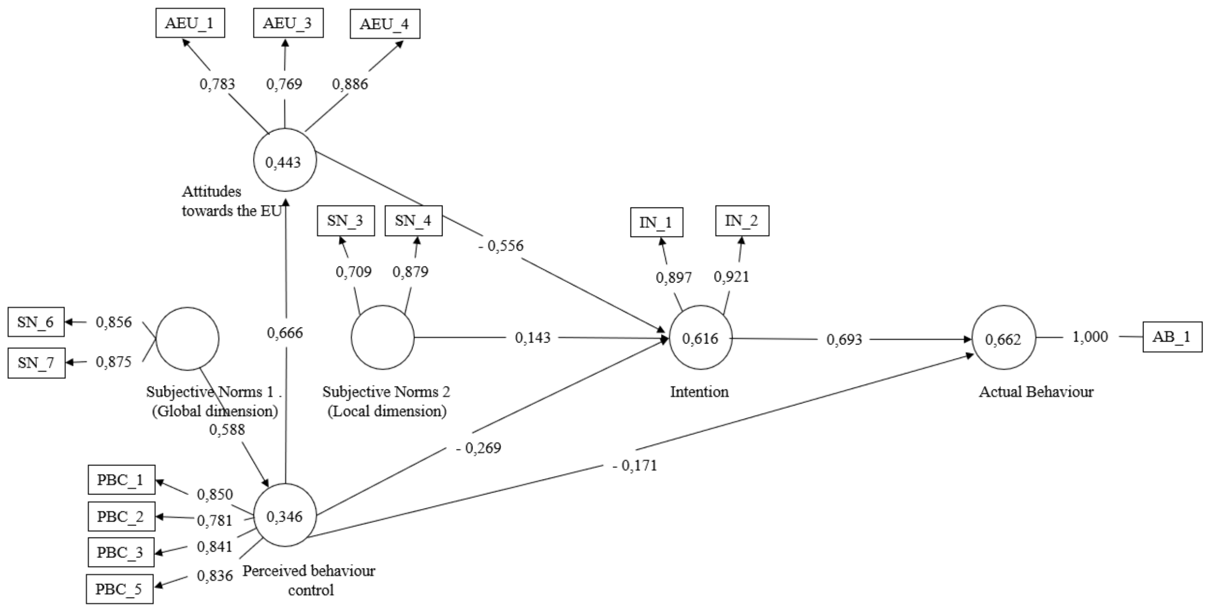

Figure 2. Measurement model.

Note that Figures 1 and 2 are not exactly the same. This is because the construct "Subjective Norms" was split into two factors or latent variables because their items measure different concepts: subjective norms associated with EU regulations (i.e. Subjective Norms 1); and subjective norms associated with social relationships (i.e. Subjective Norms 2).

The reliability of the constructs or latent variables is used to determine consistence of their indicators. That is to say, it considers simple correlations of the measurements or indicators with their respective construct and valued by examining the loads or factorial weights (λ). Loads larger than 0.707 are considered appropriate implying that indicators with lower load values should be eliminated (Hair, Ringle and Sarstedt, 2011). Figure 2 shows the items that resulted reliable. The rest were eliminated because they did not satisfy the minimum required values.

Table 5. CR and AVE indicators of the measurement model.

Construct	**Indicator**	**Individual reliability Loading λ**	**CR**	**AVE**
Actual behaviour	AB_1	1	1	1
Intention	IN_1	0.897	0.905	0.827
	IN_2	0.921		
Attitudes towards the EU	AEU_1	0.783	0.855	0.664
	AEU_3	0.769		
	AEU_4	0.886		
Perceived behavioural control	PBC_1	0.850	0.897	0.684
	PBC_2	0.781		
	PBC_3	0.841		
	PBC_5	0.836		
Subjective norms 2	SN_3	0.709	0.857	0.749
	SN_4	0.879		
Subjective norms 1	SN_6	0.856	0.773	0.632
	SN_7	0.875		

Internal consistency shows the reliability of the construct. The SmartPLS software provides the composed reliability index (CR) and the Cronbach's alpha. The former is more appropriate than the Cronbach's alpha for PLS because it does not assume the same weight for all the indicators (Chin, 1998). Nunnally and Bernstein (1994) suggest values of CR lower than 0.7 to satisfy internal consistency.

Convergent validity indicates when a set of items represent an underlying single construct which is validated by means of the AVE indicator. This indicator determines whether the variance of the construct is explained by the selected items. That is, it provides the amount of this variance in relation to the variance explained by the measurement error. A value of AVE equal or higher than 0.5 is required because it means that the selected items determine at least 50% of the variance of the construct (Hair et al., 2013).

Table 3 summarises the results showing that the individual reliability of the observable variables, composed reliability (CR), and convergent validity corresponding to the average variance extracted (AVE) are all satisfied. On the other hand, discriminant validity indicates what constructs are different from each other i.e. that variables are not related and similar and instead are distinct constructs. In order to value the discriminant validity, the Fornell-Larcker criterion (or cross loadings between the indicators of latent variables) is employed (Fornell and Larcker, 1981). This criterion considers the variance that a construct captures with its indicators (i.e. AVE), which has to be larger than the variance that this construct shares with other constructs. That is, the square root of AVE of a construct has to be larger than the correlation of this construct with another construct as shown in the following Table.

Table 6. Fornell-Larcker criterion for discriminant validity (square root values of AVE are presented in the diagonal. The other values correspond to correlations between the latent variables).

	Attitudes towards EU	**Behavior**	**Intention**	**Perceived behavior control**	**Subjective Norms**	**Subjective Norms2**
Attitudes towards EU	0.815					
Behavior	-0.696	1.000				
Intention	-0.746	0.803	0.909			
Perceived behavior control	0.666	-0.617	-0.643	0.827		
Subjective Norms	0.475	-0.390	-0.415	0.588	0.866	
Subjective Norms2	-0.081	0.139	0.197	-0.033	0.026	0.795

Following Fornell-Larcker's criterium for discriminant validity, it is concluded that the constructs are different and each measures a different concept (Hair et al., 2013; Cepeda and Roldán, 2004).

4.2.2. Fitting results of the structural model

To achieve appropriate interpretation and to draw conclusions from the model, it is necessary to carry out an evaluation of the structural model which consists of determining the path coefficients (β) obtained in Figure 2, the explained variance (R^2), the predictive relevance (Q^2), and the total effect on the endogenous constructs. First, the *t* value of the relationship between constructs is studied with the purpose of determining whether there is a statistically significant relationship. For this purpose, an equivalent of the *t*-Student statistic is estimated using a re-sampling approach that is based on the bootstrapping technique (Varian, 2005). Table 7 shows that the *t* values of the regression coefficients between the latent variables are highly significant at the 95% of confidence level. That is, if the absolute value of the *t* statistic is larger than 1.96, then the relationship is statistically significant for 95% of significant level. Consequently, the hypotheses stated in the conceptual model are supported by the data.

Table 7: Path coefficients (β) and Bootstrapping results.

Relationship between constructs	Standardised β values	*t* statistic
Attitudes towards EU → Intention	-0,556	12.678
Intention → Actual behaviour	0.693	21.600
Perceived behaviour control → Attitudes towards EU	0.666	22.951
Perceived behaviour control → Actual behaviour	-0.171	4.796
Perceived behaviour control → Intention	-0.269	6.043
Subjective Norms → Perceived behaviour control	0.588	18.625
Subjective Norms 2 → Intention	0.143	4.629

The path coefficients of standardised weights of the regression, identified by means of the arrows that link the constructs, are interpreted in the same way as the β coefficients obtained from traditional regressions and correspond to the direct effects. That is, an increase in the standard deviation of a determine construct by one unit will cause and increase of β standard deviations in the related construct. For example, for the first relationship in Table 7, if the score (in standard deviations) on “Attitudes towards the EU” increases by one unit, then “Intention” decreases in 0.556 units (in standard deviations). The same is valid for the other relationships taking into account the sign (i.e. positive means an increase and negative a decrease).

According to Chin (1998), a predictor variable should explain at least 1.5% of the characteristic to be determined for this relationship to be statistically significant.

Table 8 shows that the construct *attitudes towards the EU* (AEU) is the one with the highest predictive power in terms of variance percentage of the construct *intention* (IN). That is, the construct “Attitudes towards the EU” contributes by 41.5% of the variance of the construct “Intention” explained by the model which is calculated by multiplying the respective path coefficient β with the correlation between both constructs. The latter, in turn, is the construct with the higher predictive power for the construct *actual behaviour* (AB). The model overall explains 61.6% of IN and 66.2 % of AB. In order to evaluate the predictive relevance of the model, the Blindfolding approach by means of the Q^2 index was adopted. In this approach, a fraction of the data of a determined construct is omitted when estimating the parameters. After that, these parameters are used to estimate the omitted data (Tenenhaus et al., 2005). As shown in Table 8, the results were all positive implying that the predictive relevance of the model is satisfied.

On the other hand, the R^2 value refers to the quantity of variance of a variable that is explained by the dependent constructs. The acceptance level threshold for this indicator is 0.1.

This is because smaller numbers imply low predictive power (Falk and Miller, 1992). Table 9 shows that the four constructs have large values for the R^2 indicator meaning that a large percentage of the variance is explained by the model.

Table 8. Path coefficients (β) of each relationship with IN and AB

Construct	**Relationship (β) from the construct to IN (βIN)**	**Correlation between the construct and IN (CIN)**	**Percentage of explained variance (βIN*CIN) of IN**
Attitudes towards the EU	-0.55646	-0.746	41.5%
Perceived behavioural control	-0.269	-0.643	17.3%
Subjective norms 2	0.143	-0.197	2.8%
Total explained variance in percentage			61.6%
Construct	**Relationship (β) from the construct to AB (βAB)**	**Correlation between the construct and IN (CAB)**	**Percentage of explained variance (βAB*CAB) of AB**
Intention	0.693	0.803	55.6%
Perceived behavioural control	-0.171	-0.617	10.6%
Total explained variance in percentage			66.2%

Table 9. Predictive relevance and explained variance by the model.

Construct	**Q^2**	**R^2**
Attitudes towards EU	0.275	0.443
Actual behaviour	0.648	0.662
Intention	0.484	0.616
Perceived behaviour control	0.223	0.346

In summary, the measure model presents good psychometric properties that validate the estimation of the latent variables as the reliability and validity criteria are both satisfied. On the other hand, the structural model shows relationships that are statistically significant verifying the hypotheses proposed in the conceptual model. In addition, the predictive relevance is verified and the values of the R^2 indicator are larger than the accepted threshold for the explained variance by the model.

4.2.3. Total effect

Table 10 shows the total effect of each construct on IN and AB. According to this table, *perceived behavioural control* is the construct with the larger (negative) effect on IN, and IN is the construct with the larger (positive) effect on AB.

Total effects are calculated by adding the direct and indirect effects. For example, the total effect of "Perceived behavioural control" on "Actual behaviour" is calculated by adding the indirect effects of the mediating variables "Attitudes towards the EU" (i.e. 0.666*(-0.556)*0.693) and "Intention" (i.e. -0.269*0.693) and the direct effect (i.e. -0.171) resulting in a value equal to -0.614 (see Figure 2). Indirect effects, on the other hand, are calculated by multiplying the coefficients of the links that connect two variables that are indirectly connected through an intermediate variable that makes this connection possible.

Table 10. Total effects.

Construct	**Total effect of the construct on IN**	**Total effect of the construct on AB**
Attitudes towards EU	-0.556	-0.386
Perceived behaviour control	-0.639	-0.614
Subjective norms 1	-0.375	-0.361
Subjective norms 2	0.143	0.099
Intention		0.693

According to this result, if the standard deviation of the construct IN is increased by one unit, then the construct AB increases by 0.693 standard deviations. Similar interpretation applies to each construct.

In considering this table, it is concluded that a major result of the current investigation is the significant effect of the *perceived behavioural control* construct on intention to leave. This construct is a proxy of farmers' sense of self, identity and agency because it reflects farmers' desire to work autonomously and free from external control (see Stock and Forney, 2014). Therefore, constraints on farming business choices by EU regulations can be perceived by the farmers as constraints to self-expression. Implications of this finding are presented in the next section.

5. Discussion

This section focusses on the implications of the results obtained from the PLS-SEM approach. For this purpose, Figure 3 provides a more informative representation of the models depicted in Figures 1 and 2 and is used as the referential behavioural model for farmers' reported Brexit voting decision.

The behavioural model in Figure 3 shows the specific statements that form part of the constructs, the significant links between these constructs, and the direct effect that a construct has on another when they are linked. As explained above, the latter are reflected in the path coefficients of the regression (β) which are presented in this figure as positive or negative numbers in the arrows that link related constructs. The subjective norms were split by the software into two sets of subjective norms. The first one captures the influence of regulation at a larger scale (i.e. EU regulations faced by farmers) and is referred to in Figure 3 as *global dimension of subjective norms* (GDSN). The second set captures the influence of people that are relevant to a farmers at the local level (i.e. neighbours and social relationships in general) and is referred to in this article as *local dimension of subjective norm* (LDSN).

In relation to GDSN, this factor in explaining farmers' reported Brexit voting decision was already been noticed by Olivas-Osuna et al. (2019) (see the critique in the introduction). This means that this current research provides quantitative evidence to test the argument that many farmers voted Leave expecting that the more restrictive and bureaucratic aspects of the EU health and safety regulations would be eliminated. However, as shown in Figure 3, we found in addition that this factor did not directly affect this decision. On the contrary, there are explicit channels by which this factor influenced farmers' voting choices. This is explained as follows. According to the model, the GDSN strongly affects perceived behavioural control (β = +0.588). This means that farmers who state that they feel that they face too many regulations imposed by the EU including restrictions for example on agrochemical use believe that they have less control over the farm business when in the EU. That is, these farmers believe that EU regulations, reduce personal agency and prevent them from making higher profits or being involved in investment initiatives, or having more market power or being more confident when making farm business decisions. Thus voting for Brexit is perceived as delivering more behavioural control over their businesses than the current situation. This negative perception towards the EU in terms of the ability to control the farm, in turn, strongly affects the attitudes that farmers have on the EU (β = +0.666).

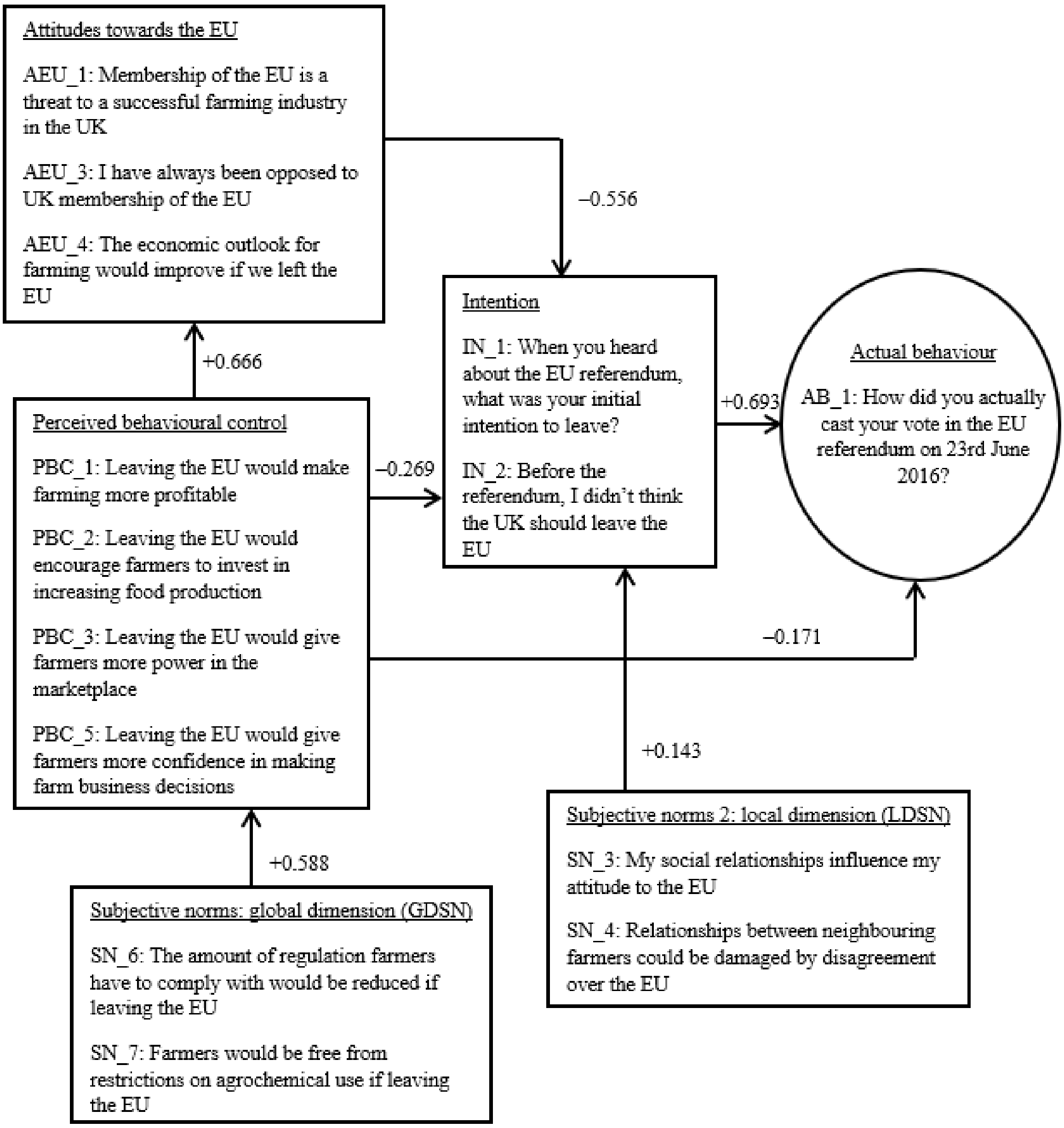

Figure 3. Behavioural model of farmers' Brexit voting decision.

In other words, farmers who believe that they have reduced agency and less control over the farm business perceive this block as a threat that can damage their own business and the farming industry and this reinforces their opposition against EU membership.

What is interesting about this finding is that GDSN is a catalyser that directly reinforces pessimist beliefs about their sense of autonomy and control over the farm and indirectly reinforces negative attitudes towards the EU. However, it did not directly affect intention nor actual behaviour. Intention was actually strongly influenced by attitudes towards the EU (β = –0.556) in the sense that farmers who stated they had stronger negative feeling about the EU had more incentives to vote leave (i.e. an increase in the Likert scale for the statements in the attitudes construct caused a decrease in the scale of intention which, as explained in Section 3, corresponds to: 1= Leave; 2=I did not vote; 3=Remain). Perceived behavioural control also directly affects intention but the effect is less strong (β = –0.269). This means that farmers who believed that they did not have control over the farm were more likely to vote leave. While this effect is smaller, it becomes stronger when adding the indirect influence of perceived behavioural control on attitudes towards the EU.

In relation to LDSN, it is observed in the research that this type of subjective norm had a positive effect on intention meaning that farmers who agreed with the statements contained in the LDSN construct were more likely to vote remain. This suggests that social relationships and the degree of contact with neighbours played a role in farmers' voting decision. However this impact is not as strong (β = +0.143) as the negative influence shown by the perceived behavioural control and attitudes towards the EU constructs. This may suggest that farmers who suggest they feel a sense of injustice, and isolation from their social communities were more likely to vote to leave the EU. Indeed Stock and Forney (2014) state that for a farmer autonomy is an integral part of being and (continuously) becoming a farmer as the business changes and develops and that there is a clear interaction between self, identity and agency. Thus perceived behavioural control as a variable identified in this study is a proxy for the farmers' sense of self, identity and agency. Autonomy has been identified as a "key trait or tool of identification central to farmers themselves and how they rationalise their behaviour and as a neoliberal attribute focused on liberty, freedom from state control, regulation and reliance on others, entrepreneurship and freedom to produce food according to market drivers (Stock et al. 2014). Indeed, they argue autonomy can be lived on the individual level or collectively as a social class, a farming class and this construct then positions feelings of self and others, of others being different and of self being isolated or threatened.

There are a number of implications that can be highlighted from this finding. Narratives related to national identity, fiscal resources and negative feelings on migrant labour (Arnorsson and Zoega, 2018; Fetzer 2018; Abrams and Travaglino, 2018) were not primarily explored in this study. Instead perceptions associated with the farmers' situated environment were explored. What the respondents identified as of importance to them was the ability to control their business and how their believed this ability was constrained, and frustrated by EU legislation. This is of interest, because it is complying with this very legislation that affords access to EU markets, and moving away from this legislation post-Brexit may well then become a barrier to trade with this market. However farmers' perceptions of an uneven level of compliance in standards adoption across EU i.e. that some countries are more equal than others when it comes to adoption of EU agricultural requirements may mediate attitudes towards the EU market. Serra and Duncan (2016) hint at a mixed experience of farming policy where the smaller farms are being forced out, there is a differentiated level of access to funding and finance and a driver for agricultural policy to be ever more focused on larger players in the industry. This study suggests that if similar legislation and policy is adopted by the UK in the future this may not be welcomed by farmers if it impacts on their agency and ability to be autonomous in their decision-making. The sense of disempowerment that some farmers feel and their reaction to it in the face of prescriptive compliance based market and regulatory governance has implications for future policy adoption and is worthy of further empirical research.

Secondly, the behavioural model developed in this article may be used to provide possible reasons for the voting choices made by the farmers when classifying them into categories. For example, more educated farmers voted remain (Table 3), although this was a trend and not a statistically significant relationship. A possible explanation is that the education they received had provided them with more knowledge about markets and the economic impact of leaving the EU on the agri-food industry. They may also have realised that leaving this trading block does not imply less regulation and this level of regulation may be replaced by similar arrangements by the UK government in the event of Brexit occurring. However, correlation does not necessarily mean cause and effect. Goodwin and Heath (2016) note that on a national level graduates who live in low-skilled communities were more likely to vote for Brexit, and their voting patterns were more similar to those with low education, than graduates who live in high-skilled communities. They suggest that this is because of a sense of "being left behind". Indeed they note "in low-skilled communities the difference in support for leave between graduates and those with GCSEs was 20 points. In high-skilled communities it was over 40 points." Thus the differential seen in this study, albeit much smaller than the Goodwin and Heath work, may not be a reflection of education level, but instead reflect this sense of being left-behind as individuals or communities. This finding too is worthy of further empirical research.

Small farmers had a tendency to report that they voted remain. Using the behavioural model, this choice may reflect the fact that these farmers feel that they are too small to benefit from any change, perhaps due to the lack of economies of scale, and/or they exhibit low trust in market relationships. Power in supply chains can have multiple attributes which are sometimes mutually exclusive. Power dynamics vary from coercion, relationship lock-in, the degree of power imbalance between different actors in the chain, and other more diffuse, oblique and systemic characteristics (Brookes et al. 2017). Manning et al. (2017) state that the interconnection between diverse pressures that operate at individual, organisational or supply chain level can lead to a complex, interlocked set of power relations. For the small farmers in this study remaining in the EU may be an option to secure themselves within this power dynamic and ensure some income via EU subsidy payments. The influence of power dynamics on farmer perceptions of their ability to be autonomous or how they interact with supply chain dynamics is worthy of further study.

6. Conclusion

The Brexit voting decision has given rise to a number of questions, especially about farmers' voting decisions. The study found that, for the sample group examined, voting choice was strongly influence by farmers' perceptions about EU legislation, their attitudes towards the EU, their perceived capacity to control factors that impact on the farm performance, and their sense of self and notions of autonomy within the confines of prescriptive agricultural policy. The sense that leaving the EU would make agricultural policy less restrictive and the farmers' need to make farming more profitable, allow for reinvestment and to have more power in markets and have more confidence in their decision making were all key drivers of their voting preference, but will this happen in practice? This research identifies a range of influences that affect farmer decision making that are worthy of further research in different contexts to see how they inform and influence wider farmer decision making. An important research question that this study presents is that if attitudes against EU regulation and perceived capacity to control factors that impact on the farm performance are key to farmers' engagement with and acceptance of regulatory and market requirements and associated policy instruments, what is it that shapes those farmer attitudes and perceptions of agency and self-identity in a largely prescriptive regulatory and market environment?

References

Ajzen, I. 1985. From intentions to actions: a theory of planned behaviour. In J. Kuhl and J. Beckman (Eds.), Action-control: from cognition to behavior. Heldelberg: Springer, 11-39.

Abrams, D. and Travaglino, G.A. 2018. Immigration, political trust, and Brexit – Testing an aversion amplification hypothesis. British Journal of Social Psychology 57, 310-326.

Alabrese, E., Becker, S.O., Fetzer, T. and Novy, D. 2019. Who voted for Brexit? Individual and regional data combined. European Journal of Political Economy 56, 132-150.

Arnorsson, A. and Zoega, G. 2018. On the causes of Brexit. European Journal of Political Economy 55, 301-323.

Becker, S.O. Fetzer, T. and Novy, D. 2017. Who voted for Brexit? A comprehensive district-level analysis. Economic Policy 32(92), 601-650.

Becker, S.O. and Fetzer, T. 2016. Does Migration Cause Extreme Voting? CAGE Online Working Paper Series 306, Competitive Advantage in the Global Economy (CAGE).

Bergevoet, R.H.M., Ondersteijn, C.J.M., Saatkamp, H.W., van Woerkum, C.M.J. and Huirne, R.B.M. (2004). Entrepreneurial behaviour of dutch dairy farmers under a milk quota system: goals, objectives and attitudes. Agricultural Systems, 80(1), 1-21.

Brakman, S., Garretsen, H. and Kohl, T. 2018. Consequences of Brexit and options for a 'Global Britain'. Papers in Regional Science 97(1). 55-72.

Brooks, S., Leaver, A., Spence, M., Elliott, C.T. and Dean, M. 2017. Pragmatic engagement in a low trust supply chain: Beef farmers' perceptions of power, trust and agency. Competition & Change 21(2), 114-131.

Cepeda, G. and Roldán, J.L. 2004. Aplicando en la práctica la técnica PLS. Congreso de la ACEDE, Murcia, España.

Chin, W.W. 1998. The partial least squares approach to structural equation modeling. Modern methods for business research 295(2), 295-336.

Clarke, H.D., Goodwin, M. and Whiteley, P. 2017. Parliamentary Affairs 70(3), 439-464.

Deng, J., Sun, P., Zhao, F., Hana, X.,Yang, G. and Feng, Y. 2016. Analysis of the ecological conservation behavior of farmers in payment for ecosystem service programs in eco-environmentally fragile areas using social psychology models. Science of the Total Environment 550, 382-390.

Dhingra, S., Ottaviano, G., Rappoport, V., Sampson, T. and Thomas, C. 2018. UK trade and FDI: A post-Brexit perspective. Papers in Regional Science 97(1). 9-25.

Dhingra, S., Machin, S. and Overman, H.G. 2017. Local economic effects of Brexit. National Institute Economic Review 242(1), R24-R36.

Dhingra, S., Ottaviano, G., Sampson, T. and Van Reenen, J. 2016. The consequences of Brexit for UK trade and living standards. CEP BREXIT paper no. 02. London School of Economics.

Dibbern, J., Goles, T., Hirschheim, R. and Jayatilaka, B. 2004. Information systems outsourcing: a survey and analysis of the literature. DATABASE for Advances in Information Systems 35(4), 6-102.

Esposito Vinzi, V. and Russolillo, G. 2010. Partial least squares path modeling and regression. In: Wegman, E., Said, Y. and Scott, D. (Eds.), Wiley Interdisciplinary Reviews: Computational Statistics. Wiley, New York.

Falk, F. and Miller, N. 1992. A Primer for Soft Modeling. University of Akron Press, Akron.

Fetzer, T. 2018. Did Austerity Cause Brexit?, CESifo Working Paper, No. 7159, Center for Economic Studies and Ifo Institute (CESifo), Munich.

Fornell, C. and Larcker, D. 1981. Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research 18(1), 39–50.

Forss, K., and Magro, L. 2016. Facts or feelings, facts and feelings? The post-democracy narrative in the Brexit debate. European Policy Analysis, 2(2), 12-17.

Garretsen, H., Stoker, J.I., Soudis, D., Martin, R.L. and Rentfrow, P.J. 2018. Brexit and the relevance of regional personality traits: more psychological Openness could have swung the regional vote. Cambridge Journal of Regions, Economy and Society 11(1), 165-175.

Golec de Zavala, A., Guerra, R. and Simão, C. 2017. The Relationship between the Brexit Vote and Individual Predictors of Prejudice: Collective Narcissism, Right Wing Authoritarianism, Social Dominance Orientation. Frontiers in Psychology 8, 2023.

Goodwin, M. and Heath, O. 2016. Brexit vote explained: poverty, low skills and lack of opportunities. Available at https://www.jrf.org.uk/report/brexit-vote-explained-poverty-low-skills-andlack-opportunities (accessed 14 March 2019).

Hair, J., Ringle, C. and Sarstedt, M. 2013. Editorial-partial least squares structural equation modeling: rigorous applications, better results and higher acceptance. Long Range Planning 46 (1-2), 1–12.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M. and Thiele, K.O. 2017. Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. Journal of the Academy of Marketing Science, 45(5), 616–632.

Hearne, D., Semmens-Wheeler, R. and Hill, K.M. 2019. Explaining the Brexit Vote: A Socioeconomic and Psychological Exploration of the Referendum Vote, in Alex de Ruyter, Beverley Nielsen (ed.) Brexit Negotiations After Article 50: Assessing Process, Progress and Impact (Brexit Studies Series, Volume), 89-111.

Henderson, A., Jeffery, C., Wincott, D. and Jones, R.W. 2017. How Brexit was made in England. British Journal of Politics & International Relations 19(4), 613-646.

Henseler, J., Hubona, G. and Ash Ray, P. 2016. Using PLS path modeling in new technology research: updated guidelines. Industrial Management & Data Systems 116(1), 2-20.

Hobolt, S.B. 2016. The Brexit vote: a divided nation, a divided continent. Journal of European Public Policy 23(9), 1259-1277.

Hozić, A.A. and True, J. 2017. Brexit as a scandal: gender and global trumpism, Review of International Political Economy 24(2), 270-287.

Kierzenkowski, R., Pain, N., Rusticelli, E. and Zwart, S. 2016. The Economic Consequences of Brexit: A Taxing Decision", OECD Economic Policy Papers, No. 16, OECD Publishing, Paris.

Lee, N., Morris, K. and Kemeny, T. 2018. Immobility and the Brexit vote. Cambridge Journal of Regions, Economy and Society 11(1), 143-163.

Lévy, J. and Varela, J. 2006. Modelación con Estructuras de Covarianzas en Ciencias Sociales. España, Madrid: Editores Netbiblo.

Liberini, F., Oswald, A.J., Proto, E. and Redoano, M. 2017. Was Brexit Caused by the Unhappy and the Old?. IZA Discussion Paper No. 11059. Institute of Labor Economics (IZA), Bonn.

Los, B., McCann, P., Springford, J. and Thissen, M. 2017. The mismatch between local voting and the local economic consequences of Brexit. Regional Studies 51(5), 786-799.

Manners, I. 2018. Political Psychology of European Integration: The (Re)production of Identity and Difference in the Brexit Debate. Political Psychology 39(6), 1213-1232.

Manning, L. Soon. J.M., Aguiar, L.K., Eastham, J.F. and Higashi, S.Y. 2017. Pressure: driving illicit behaviour in the food supply chain 12th Research Workshop on Institutions and Organisations (12th RWIO) Brazil 10-11 July 2017.

Marcoulides, G. and Saunders, C. 2006. PLS: A silver bullet? Management Information Systems Quarterly 30(2), 3-9.

Martínez, M and Fierro, E. 2018. Application of the PLS-SEM technique in Knowledge Management: a practical technical approach. Ride 8(6), DOI: 10.23913/ride.v8i16.336.

May, D., Arancibia, S., Behrendt, K., and Adams, J. 2019. Preventing young farmers from leaving the farm: Investigating the effectiveness of the young farmer payment using a behavioural approach. Land Use Policy 82, 317-327.

May, D.E. 2012. Non-Economic Drivers Influencing Farmers' Incentives to Cooperate: Do they Remain Robust Through Policy Changes? Journal of Rural Cooperation 40(2), 217-238.

McGuinness, T. and Grimwood, G.G. 2017. Migrant workers in agriculture. Briefing Paper 7987. House of Commons Library.

Morais, M., Binotto, E. and Borges, J.A.R. 2017. Identifying beliefs underlying successors' intention to take over the farm. Land Use Policy 68, 48-58.

Nakagawa, Y. 2018. Psychological and Behavioral Predictors of Rural In-migration. Rural Sociology 83(1), 24–50.

Olivas-Osuna, J.J., De Lyon, J., Gartzou-Katsouyanni, K., Bulat, A., Kiefel, M., Bolet, D., Jablonowski, K. and Kaldor, M. 2019. Understanding Brexit at a local level: causes of discontent and asymmetric impacts. London School of Economics and Political Science, London, UK.

O'Reilly, J., Froud, J., Johal, S., Williams, K., Warhurst, C., Morgan, G., Grey, C., Wood, G., Wright, M., Boyer, R., Frerichs, S., Sankari, S., Rona-Tas, A. and Le Galès, P. 2016. Brexit: understanding the socio-economic origins and consequences. Socio-Economic Review 14(4), 807–854.

Pavlou, P. and Chai, L. 2002. What drives electronic commerce across cultures? A crosscultural empirical investigation of the theory of planned behaviour. Journal of Electronic Commerce Research 3(4), 240-253.

Portes, J. and Forte, G. 2017. The Economic Impact of Brexit-induced Reductions in Migration.Oxford Review of Economic Policy 33(Supplement 1), S31–S44.

Reinartz, W., Krafft, M. and Hoyer, W. 2004. The customer relationship management process: its measurement and impact on performance. Journal of Marketing Research 41(3), 293-305.

Ringle, C.M., Wende, S. and Becker, J.M. 2015. SmartPLS 3. Boenningstedt: SmartPLS GmbH. http://www.smartpls.com.

Rodríguez-Entrena, M., Salazar-Ordóñez, M. and Samir, S. 2013. Applying partial least squares to model genetically modified food purchase intentions in southern Spain consumers. Food Policy 40, 44-53.

Roldan, J. and Cepeda, G. 2016. Modelos de Ecuaciones basados en la Varianza: Partial Least Squares (PLS) para Investigadores en Ciencias Sociales (3a ed.). Apuntes del curso en la Universidad de Sevilla, España.

Salganik, M.J. and Douglas, D.H. 2004. Sampling and estimation in hidden populations using respondent-driven sampling. Sociological Methodology 34(1), 193-239.

Sampson, T. 2017. Brexit: The Economics of International Disintegration. Journal of Economic Perspectives 31(4), 163-184.

Serra, A., and Duncan, J. 2016, February. European farmers and the “Greening” of the CAP: A Critical Discourse Analysis. In *Colloquium paper* (No. 13). Available at: https://www.iss.nl/sites/corporate/files/13-ICAS_CP_Serra_and_Duncan.pdf

Stock, P. V., Forney, J., Emery, S. B., and Wittman, H. 2014. Neoliberal natures on the farm: farmer autonomy and cooperation in comparative perspective. Journal of Rural Studies, 36, 411-422.

Stock, P.V. and Forney, J. 2014. Farmer autonomy and the farming self. Journal of Rural Studies 36, 160-171.

Swales, D. and Baker, S. 2016. The impact of Brexit on the UK agricultural workforce. Horizon, AHDB.

Tenenhaus, M., EspositoVinzi,V., Chatelin,Y.M. and Lauro, C.2005. PLSpathmodeling. Computational Statistics & Data Analysis 48(1), 159-205.

The Electoral Commission (2019). Results and turnout at the EU referendum. Available at: https://www.electoralcommission.org.uk/who-we-are-and-what-we-do/elections-and-referendums/past-elections-and-referendums/eu-referendum/results-and-turnout-eu-referendum

Varian, H. 2005. Bootstrap tutorial. Mathematical Journal 9(4), 768-775.

Appendix A: Questionnaire

I. Profile questions

Please select the word or phrase that best matches your response.

What is your gender?

- ☐ Male
- ☐ Female

What is your age?

- ☐ Under 25
- ☐ 25-34
- ☐ 35-44
- ☐ 45-54
- ☐ 55-64
- ☐ 65 or more

What is your highest level of education?

- ☐ A level of further education equivalent
- ☐ GCSE or equivalent
- ☐ Degree
- ☐ Postgraduate
- ☐ Other

What it is your role in the farm?

- ☐ Employer manager
- ☐ Holder, partner, director
- ☐ Other family member
- ☐ Unwaged family labour
- ☐ Waged labour
- ☐ Retired
- ☐ None of the above

In what region is located the farm where you work?

- ☐ East Midlands
- ☐ East of England
- ☐ North East
- ☐ North West
- ☐ West Midlands
- ☐ Yorkshire and Humberside
- ☐ South East
- ☐ South West
- ☐ Northern Ireland
- ☐ Wales
- ☐ Scotland
- ☐ Other

What farming activity is developed in the farm?

- ☐ Cereals
- ☐ Dairy
- ☐ General cropping
- ☐ Lowland Grazing Livestock
- ☐ Upland Grazing Livestock
- ☐ Pigs/Poultry
- ☐ Mixed
- ☐ Other

Type of tenure?

- ☐ Mainly owned
- ☐ Mainly tenanted
- ☐ Owner-occupied
- ☐ Tenant

Number of hectares in the farm?

- ☐ 0-150
- ☐ 151-300
- ☐ 301-450
- ☐ 451 or more

II. Statements

Use the scale below to indicate the option that best represent your opinion in relation to the following statements.

Strongly disagree (1)	Disagree (2)	Indifferent (3)	Agree (4)	Strongly agree (5)

a) Membership of the EU is a threat to a successful farming industry in the UK	
b) The free movement of goods and people between EU member states is a good thing	
c) I have always been opposed to UK membership of the EU	
d) The economic outlook for farming would improve if we left the EU	
e) Membership of the EU required surrendering our national identity	
f) Membership of the EU causes a negative impact on jobs and public services	
g) The Brexit debate produced much propaganda and little reliable analysis	
h) I considered the evidence on both sides of the Brexit debate before deciding how to vote	
i) My social relationships influence my attitude to the EU	
j) Relationships between neighboring farmers could be damaged by disagreement over the EU	
k) It is important to be well informed before taking important decisions	
l) The amount of regulation farmers have to comply with would be reduced if leaving the EU	
m) Farmers would be free from restrictions on agrochemical use if leaving the EU	
n) Leaving the EU would make farming more profitable	
o) Leaving the EU would encourage farmers to invest in increasing food production	
p) Leaving the EU would give farmers more power in the marketplace	
q) Leaving the EU would decrease risk and uncertainty in the farming sector	
r) Leaving the EU would give farmers more confidence in making farm business decisions	
s) Leaving the EU would prevent farmers from employing EU migrant labour	
t) Before the referendum, I didn't think the UK should leave the EU	

III. Question reflecting intention to leave

Use the scale below to indicate your answer to the following question:

When you heard about the EU referendum, what was your initial intention to leave?

Leave (1)	Undecided (2)	Remain (3)

IV. Question reflecting actual behaviour

Use the scale below to indicate your answer to the following question:

How did you actually cast your vote in the EU referendum on 23rd June 2016?

Leave (1)	I did not vote (2)	Remain (3)

Appendix B: Analysis of sociodemographic variables

Several tests were carried out to determine significant effects (i.e. standardised path coefficient) of sociodemographic variables (measured as dummy variables in order to reflect the categories presented in the profile questions in Appendix A) on both intention and actual behaviour constructs. No significant effects were found for a 5% of significance level (i.e. the absolute value of the *t* statistic under the bootstrapping method is smaller than 1.96). This is illustrated in Tables B1 and B2 which include the dummy variables of the categories with the higher frequency for each sociodemographic variable (e.g. gender, education, etc.).

Table B1. Statistical effect of sociodemographic dummy variables on actual behaviour.

Direct relationships of the model	Standardized path coefficient	Standard deviation (STDEV)	Value | *t* |	P Value
Role in the farm -> Actual Behavior	-0.006	0.026	0.219	0.827
Gender -> Actual Behavior	0.014	0.026	0.513	0.608
Age -> Actual Behavior	0.000	0.027	0.004	0.997
Education-> Actual Behavior	-0.021	0.025	0.817	0.414
Region-> Actual Behavior	-0.024	0.028	0.827	0.408
Farms Types-> Actual Behavior	0.006	0.025	0.237	0.813
Tenure-> Actual Behavior	-0.027	0.025	1.078	0.281
Hectares> Actual Behavior	-0.048	0.025	1.882	0.062

Table B2. Statistical effect of sociodemographic dummy variables on intention.

Direct relationships of the model	Standardized path coefficient	Standard deviation (STDEV)	Value | t |	P Value
Role in the farm -> Intention	-0,028	0,027	1,028	0.304
Gender -> Intention	0,034	0,027	1,247	0.212
Age -> Intention	-0,023	0,028	0,808	0.419
Education-> Intention	-0,015	0,027	0,575	0.565
Region-> Intention	0,029	0,028	1,055	0.292
Farms Types-> Intention	0,019	0,027	0,708	0.479
Tenure-> Intention	-0,008	0,027	0,299	0.765
Hectares> Intention	-0,025	0,026	0,980	0.327