The influence of information sources on inter- and intra-firm diffusion: evidence from UK farming

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ABSTRACT

We study the effect of different information sources on diffusion between and within companies. Our model of economically optimising farmers replicates results from dual process persuasion theory, and predicts that inter-firm diffusion will be primarily affected by reliable, easily accessible information while intra-firm diffusion will be influenced by technical information. The results are tested on UK farming data. Consistent with our model, information from agents, suppliers, farmers, and agricultural magazines influences inter-firm adoption, from buyers influences intra-firm adoption, and from crop consultants, academics, government, and an industry body influences both.

Keywords

Innovation,

Intra-firm diffusion,

Information acquisition,

Organic farming,

Dual process persuasion theory

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1. Introduction

Inter-firm technology diffusion is the process of technological spread between companies, while intra-firm diffusion is the process of spread within companies. Recent studies in the industrial economics literature have compared determinants of the two (Battisti et al, 2007; Battisti and Stoneman, 2003; Battisti et al, 2005; Fuentelsaz et al, 2003; Hollenstein and Woerter, 2008). A promise of the work is that it can illuminate the mechanisms driving intra-firm diffusion by contrast with the more extensively investigated inter-firm diffusion.

A determinant neglected in the industrial economics literature is the role of sources providing information about technology. The determinant is important for many reasons. Information provision is a primary means of governmental influence on technology adoption (Stoneman and David, 1986). UK companies spent an estimated UK£7.6 billion in 2005 on management consultancy, with a fifth on IT-related consultancy alone (Marrano and Haskel, 2006). The management consultancy industry employs tens of thousands of UK workers (Marrano and Haskel, 2006). Prominent theories of intra-firm diffusion emphasise how information acquisition can explain diffusion (Mansfield, 1968; Stoneman, 1981), and the potential role of learning is recognised in the empirical intra-firm literature even when it is not a primary concern (Battisti and Stoneman, 2005).

Unlike the industrial economics literature, the agricultural economics literature has treated the issue to an extent, reflecting the debates on governmental extension programs (Anderson and Feder, 2004; Evenson, 2001), the large expenditures on information acquisition (Ortmann et al, 1993), the sizable advertising and outreach budgets by input suppliers (Gloy et al, 2000), and the large number of information providers (the UK Association of Independent Crop Consultants website www.aicc.org.uk reports 244 members in August 2013). The literature has treated the choice of information by farmers (Foltz et al, 1996; Gloy et al, 2000; Wolf et al, 2001), the role of information in initial adoption (Garcia-Jimenez et al. 2011; Lapple and Van Rensberg, 2011; Wozniak, 1993), and determinants of sequential adoption (Aldana et al, 2011; Khanna, 2001). Yaron et al (1992) look at how extension services affect an index including thoroughness of adoption of five farming technologies. Most relevant to our paper is Genius et al (2006), who look at partial or full adoption of organic farming with active or passive information collection as determinants of the extent of adoption, and as jointly determined variables.

The prior work in both the industrial and agricultural literature leaves much unknown about how information affects inter-firm and intra-firm diffusion. In this paper, we examine the comparative impact of information sources on inter and intra diffusion in more detail. We aim to distinguish the impact by the amount and character of the information, with our results formulated in comparative terms between the two types of diffusion.

We start by presenting our theoretical model. It describes learning about, and how to use, a technology through information acquisition. Learning is Bayesian, following the normal-normal updating in Stoneman (1981), Young (2009), and Aldana et al (2011), and with information characterised by its updating parameters. The model identifies an inter-firm stage where the company learns that a new technology is profitable and an intra-firm stage where the company learns how to use it profitably. Information sources are costly to use and their selection is based on profit maximisation.

Our model produces results similar to those in dual process persuasion theory (Petty and Cacioppo, 1986; Chaiken, 1980; Kruglanski and Thompson, 1999). It implies that different sources of information will be influential at the inter-firm and intra-firm stages. In inter-firm diffusion, information's value arises from small increases in expected returns from undertaking a technological trial. As its value is often low prior to adoption, it will be used to assess the value of a trial if it does not require expensive processing to use. Thus, reliable or readily accessible information from sources like suppliers, government, farmers, and agricultural magazines will be influential on inter-firm adoption.

For intra-firm adoption, information's value can be large if it significantly improves the use of the technology, and so the extent of adoption. An expensive but value-creating source will be preferentially used to evaluate levels of intra-firm adoption over an inexpensive but non-informative one. Such value-creating sources plausibly include buyers, consultants, academics, and government.

We test our model using a cross section 574 UK farmers surveyed in 2007, looking at the extent of their adoption of organic farming technologies. It also contains demographic data, and description of the information sources that they use. Our empirical specifications allow both for information exogeneity and endogeneity. In the former case, we run probit and linear models, and in the latter case we use bivariate probit and treatment effect models. We find that our theoretical results on inter-firm and inter-firm technology adoption hold. Specifically, we find that information from agents, suppliers, farmers, and agricultural magazines is mainly influential on inter-firm adoption. Information from buyers is largely used for intra-firm adoption, while information from crop consultants, academics, government, and an industry body is used for both forms of diffusion.

We make a number of theoretical contributions. The paper presents a new model of inter-firm and intra-firm diffusion including information usage. Unlike previous models of technology adoption using dual process persuasion theory (Angst and Agarwal, 2009; Bhattacherjee and Sanford, 2006; Bhattacherjee and Sanford, 2009; Moser and Mosler, 2008), we derive its results as an outcome of optimising economic behaviour prior to testing them. The model is the first of which we aware to allow prediction of the disaggregated information sources used in technological adoption, and it demonstrates qualitative differences in information sources used in the two diffusion stages.

Empirically, the paper demonstrates the validity of the theoretical model in the case of UK organic farming adoption, and determines which information sources affect diffusion to a more detailed degree than in prior work. The results readily lead to contrasts and complementarities with existing literature, and implications for further work and policy.

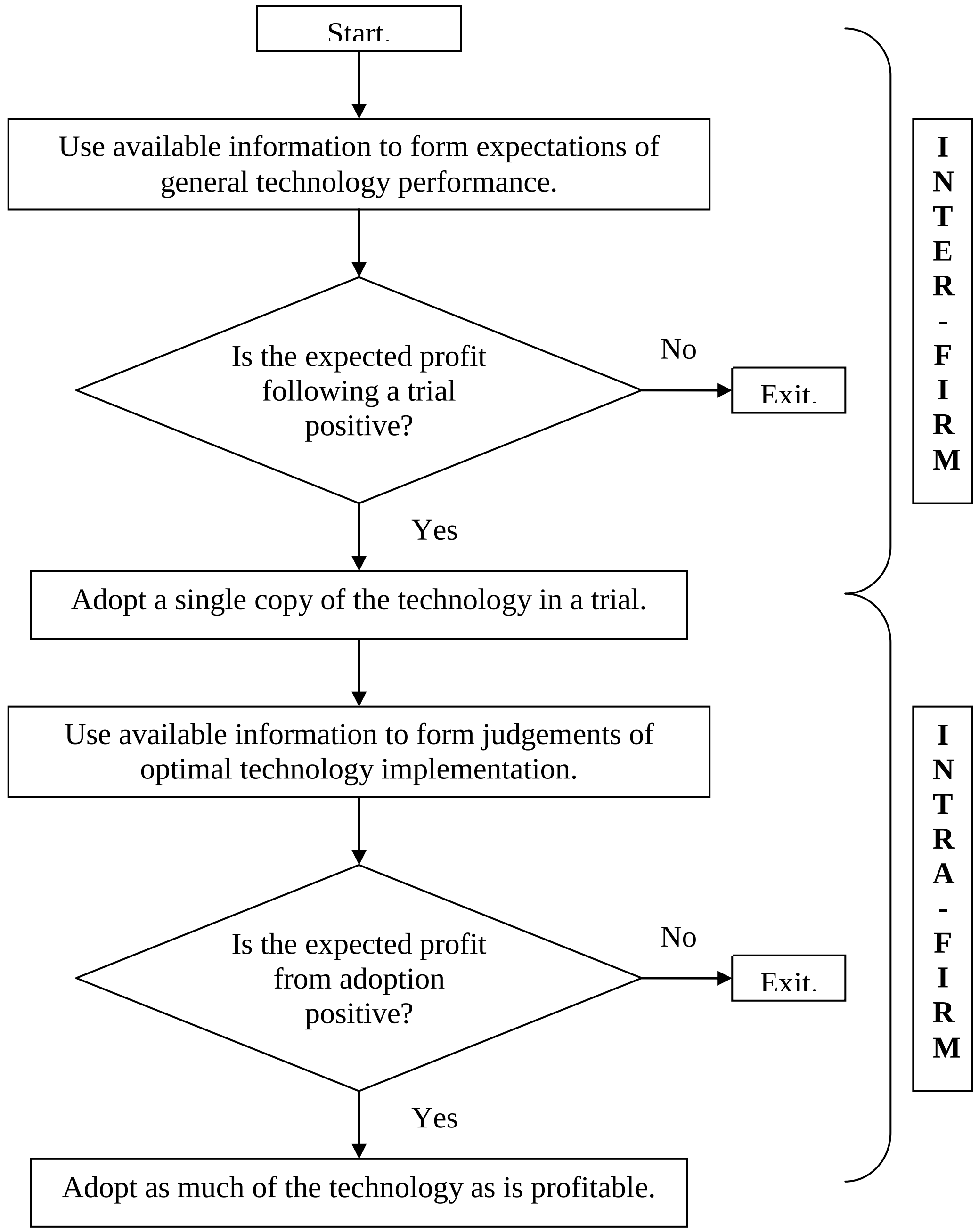
Section two looks at our theoretical framework and section three describes our data. Section four presents our estimation procedure, results are in section five, and section six concludes.

2. Theoretical framework

In this section we present our theoretical framework on adoption in the presence of information, and the hypotheses that follow from it. Our model is based on Bayesian learning, as is common in the literature (Baerenklau, 2005; Bandiera and Rasul, 2006; Conley and Udry, 2001; Foster and Rosenzweig, 1995; Grossman et al, 1977; Leathers and Smale. 1991; Kihlstrom, 1976). In particular we use the normal-normal updating of Stoneman (1981), Young (2009), and Aldana et al (2011). Different types of information are characterised by their updating effects. Our model allows for prediction of which information types influence inter-firm and intra-firm adoption.

Our results are similar to those produced in dual approach persuasion theory, such as the Elaboration Likelihood Model (Petty and Cacioppo, 1986; Petty and Wegener, 1999) and the Heuristic-Systematic Model (Chaiken, 1980; Chen and Chaiken, 1999). Broadly, in these dual process models people may be persuaded by either rational processing or heuristic cues. Rational processing requires more effort, and greater personal involvement in the outcomes is more likely to result in it (Johnson and Eagly, 1989; Petty et al, 1983). Heuristic cues include perceptions of message source reliability, and are followed when there is less receiver involvement in the outcome. In our model, inter-firm diffusion necessitates less information processing for cost reasons, and sources are heuristically selected based on their perceived reliability. Intra-firm diffusion involves higher returns and the company is more involved in the outcomes, so spends more time undertaking rational processing and analysing source information.

Figure 1: Flowchart of information use and adoption decisions



The framework is given in two sections, with the first describing inter-firm adoption and the second describing intra-firm diffusion. The scheme is shown in the flowchart in Figure 1.

Inter-firm adoption

There is a risk neutral, profit maximising company which can produce a good by using a new technology. The expected profit from use of the first copy of the technology is *P*, net of technology acquisition and other costs.

The company is unaware of the expected profit *P*, and thinks that it has a distribution $N(p, s^2)$, where $p << 0$. It receives information about *P* from a source which costs *c* to use. The information does not allow the company to evaluate the expected profit *P* perfectly. The company takes the information to be a sample *X* from the distribution $N(P, S^2)$. When information is received, the company updates its subjective distribution of *P* by Bayes' rule for each piece of information. After evaluating the information, the company can adopt one copy of the technology on a trial basis. The trial costs *k* and reveals the value of *P*.

The company has a prior distribution for *P* of $N(p, s^2)$, and a sample *X* from a likelihood distribution of $N(P, S^2)$. Using standard results on Bayesian updating, the posterior mean is

$$\mu(X) = \frac{\frac{p}{s^2} + \frac{X}{S^2}}{\frac{1}{s^2} + \frac{1}{S^2}} = \frac{S^2}{s^2 + S^2} p + \frac{s^2}{s^2 + S^2} X$$

and the posterior variance is

$$\sigma^2 = \frac{1}{\frac{1}{s^2} + \frac{1}{S^2}}.$$

It follows that, after inclusion of information, the expected income from production using the technology has a distribution $N(\mu(X), \sigma^2)$. A trial will result in investment if the expected income is revealed to exceed zero. Using standard results on censored normal distributions (see Greene

(2008), pp.870-1), the expected value to the company from a trial is $\mu(X)\Phi(\mu(X)/\sigma)+\sigma\phi(\mu(X)/\sigma)$.

A trial will be undertaken if the expected profit exceeds *k*, the cost of a trial. The value of the option to undertake a trial is thus $\max(\mu(X)\Phi(\mu(X)/\sigma)+\sigma\phi(\mu(X)/\sigma)-k,0)$, taking the value of *X* as given. Integrating over the distribution of *X* gives the expected value of the information as $\int \max(\mu(X)\Phi(\mu(X)/\sigma)+\sigma\phi(\mu(X)/\sigma)-k,0)\exp(-(X-P)^2/2s^2)/\sqrt{2\pi s^2}\,dX$. The value of the information is strictly positive as for sufficiently large *X*, the value of the first term is certain to exceed *k*. The information will be used if its value exceeds its cost, *c*, so any information that is sufficiently cheap will be used. We expect information that can be used without much effort validating it will be inexpensive to use. Such information may come from reliable sources whose information is accepted without extensive checking. We may expect reliable sources to include crop consultants, extension agents, academics, government agencies, and professional bodies. Readily accessible (and therefore inexpensive) information may also be expected from sources including farmers and agricultural magazines.

Intra-firm diffusion

We next present our model of information's effect on intra-firm diffusion. For notational convenience, we recycle the English and Greek letters used in the inter-firm model.

During the trial, the company learns how to use the technology and decides on the appropriate adoption level. The company uses the technology by selecting numbers to form an m-vector $V=(v_1,...,v_m)$. Each combination can be used to produce the first copy of the good at vector specific cost, $C(v_1,...,v_m)$. Subsequent copies are subject to rising marginal costs, so that the cost C_n of the nth good satisfies $C_n = k(n)C_1$ for some set of constants *k*(*n*), where $k(n)>k(n-1)\ \forall n>1$. The minimal starting cost *K* is attained for an optimal technology use corresponding to setting $V=\tilde{\mu}=(\mu_1,...,\mu_m)$.

Once the trial starts, the company is initially unsure of the optimal use of the technology and assumes that it has a multivariate normal distribution $N(\tilde{r},diag(s_1{}^2,...,s_m{}^2))$, where $\tilde{r}=(r_1,...,r_m)$ and $diag(s_1{}^2,...,s_m{}^2)$ is the square *m* by *m* matrix with diagonal elements $(s_1{}^2,...,s_m{}^2)$ and zeros elsewhere. When the company sets the i^{th} technology component at r_i when there is uncertainty measured by variance s_i^2, it expected to incur additional inefficiency costs equal to the variance. Thus, the total expected costs are $K + \sum_i s_i^2$.

An information source provides evidence about the optimal use, giving technical information about one or more of the vector components. The source costs c to use. A source giving information about the i^{th} component generates a single sample distributed around the optimal value of μ_i. The information does not itself allow exact evaluation, but only reviews μ_i with an error. The company perceives the sample as drawn from a distribution $N(\mu_i, \sigma_i^2)$. On receiving it, the company updates its subjective view of the distribution of μ_i using Bayes' rule. It then decides how much of the technology to adopt based on the available information, and a fixed market price for the product of P.

The company has a prior distribution $N(r_i, s_i^2)$ for the i^{th} technology component, and receives information giving a sample with a likelihood function $N(\mu_i, \sigma_i^2)$. From standard Bayesian posterior results, the posterior variance is

$$S_i^2 = \frac{1}{\dfrac{1}{s_i^2} + \dfrac{1}{\sigma_i^2}}.$$

Thus, the variance falls after including the information. The expected costs for the first copy of the good also fall to $K + S_i^2 + \sum_{j \neq i} s_j^2$, and because $C_n = k(n)C_1$ the costs of all later produced goods fall proportionately. Thus, the level of production (and hence adoption) at which costs equal the constant profit (that is, the n at which $C_n = P$) rises as information is included.

If the source is highly informative about how to use one or more technological component, then the decline in production costs may be large enough to offset even quite large implementation costs, c. Such sources will affect the level of intra-firm adoption, whereas cheap sources that do not provide implementation information will not affect intra-firm adoption. Expensive, informative sources are likely to include consultants, academics, buyers, and possibly government and professional bodies.

3. Data

The data used in this study is from a survey of pest management practices by UK farmers (Bailey, 2012) as part of the Rural Economy and Land Use Programme under sponsorship by the Economic and Social Research Council, the Biotechnology and Biological Sciences Research Council, and the Natural Environment Research Council. The survey asked farmers about their use of pesticide and alternative pest control technologies, their sources of information about farm management, their business and personal characteristics, and their attitudes to the technologies. The survey was sent in 2007 to 7,500 randomly selected names drawn from a list of UK recipients of a farming newsletter, from which there were 574 usable responses. We are unaware of any specific bias in the responses although it may exist.

The survey contains questions on the extent of use of seventeen pest control technologies, besides pesticide. The technologies can be functionally grouped as in Bailey (2009) and Bailey et al (2009). They classify them into portfolios belonging to “intra-crop bio-controllers”, “chemical ‘users’ / conservers”, “extra-crop conservation bio-controllers”, and “weed focussed farmers”. There is overlap between the first two portfolios, with pheromone monitoring / control and different varieties in different fields occurring in both[1]. The groupings are shown in Table 1.

[1] Bailey (2009) reports the overlap between groups, and we use it here. However, the source research Bailey et al (2009) does not have overlap, and we are likely to remove it in future drafts.

Table 1

Alternative pest control technologies and their portfolio groupings, with abbreviations in brackets

Intra-crop bio-controllers (Intracrop)
i) Using a trap crop (TRAPCROP)
ii) Using mixed varieties in each field (MIXEDVAR)
iii) Introducing predators/parasites of insect pests (INTROBUG)
iv) Using pheromones for monitoring insects (PHRMONIT)
v) Using pheromones for controlling insects (PHRCNTRL)
vi) Using different varieties in different fields (DIFFRVAR)
Chemical ‘users’ / conservers (Chemical)
i) Using pheromones for monitoring insects (PHRMONIT)
ii) Using pheromones for controlling insects (PHRCNTRL)
iii) Using different varieties in different fields (DIFFRVAR)
iv) Planting disease- or insect-resistant varieties (RESISVAR)
v) Spot or patch spraying (SPOTSPRA)
vi) Treating seeds/seedlings to protect crop in early stages (TRTSEEDS)
vii) Rotating pesticide classes to avoid resistance (ROTACLAS)
Extra-crop conservation bio-controllers (Extracrop)
i) Improving field margins to encourage beneficial insects (FIELDMAR)
ii) Using flower strips to encourage beneficials (FLOWERST)
iii) Using beetle banks (BEETBANK)
Weed focussed farmers (Weed)
i) Cultivation or using rotary hoe for weeds (CULTWEED)
ii) Rotating crops specifically to prevent pest problems (ROTACROP)
iii) Adjusting time of planting or other practices specifically to avoid pests (TIMEPLAN)
iv) Hand rogueing (HANDROGU)

Table 2

Commitment to use of alternative pest control technologies

1 = Not adopted and will not adopt
2 = Not adopted but will consider adoption
3 = Adopted but not currently used
4 = Adopted and currently used

For each practice, the commitment to use by each farmer is measured on scale of one to four. The meanings of each number are shown in Table 2. There are 39 farmers who omit any statement about their commitment to use the technologies and a further seven who do not code for at least one of the technologies. We exclude them from our analysis. It is possible that they are uncertain about their past or future behaviour. Another possibility is that they have never adopted and never intend to, and should be classified as unity for all technologies. However, the possibility is less plausible if we examine the numbers of technologies that each farmer has committed to never using, where the data is not entirely missing. Table 3 shows the distribution of farmers by technology exclusion. Most farmers rule out relatively few technologies, with almost a quarter ruling out no technologies and half excluding two or less. Only 14 percent exclude more than half of the technologies. So it seems unlikely that many farmers who omit their data would exclude all of the technologies. We also exclude a further six farmers who have missing data on other variables used in our analysis. There remain 522 observations.

Table 3

Distribution of farmers by the number of technologies they have not used and never intend on using

Number	Frequency	Number	Frequency
0	23.9	9	2.6
1	14.1	10	2.3
2	11.1	11	1.9
3	10.6	12	2.8
4	6.1	13	1
5	5.2	14	1.6
6	5.9	15	1.2
7	5.6	16	0.2
8	3.8		

For each pest control portfolio and farmer, inter-firm adoption is calculated as one if the farmer has ever adopted any of the technologies in the portfolio and zero otherwise. The level of adoption is shown in Table 4. The chemical user and weed focussed portfolios are most widely adopted with 95 percent and 93 percent adoption respectively. The intra-crop bio-controller and extra-crop bio-controller adoption rates are a little lower at 75 and 78 percent. Thus, there is a widespread inter-firm adoption of the portfolios.

Table 4

Numbers of farmers who have ever adopted at least one technology from each pest control portfolio

Portfolio	Not adopted	Adopted	Total	Adoption rate
Intracrop	128	394	522	75%
Chemical	27	495	522	95%
Extracrop	117	405	522	78%
Weed	35	487	522	93%

We calculate the extent of intra-firm adoption within each portfolio by summing the number of technologies within the portfolio that the farmer has ever adopted (so have commitments to use of three or four). We summarise the extent of use in Table 5. Distributional statistics are shown for each portfolio, with percentages showing the statistics divided by the number of technologies in the portfolio. Mean intra-firm adoption rates are lower than inter-firm rates, ranging from 26 percent for the intra-crop bio-controller portfolio to 67 percent for the weed focussed portfolio. Thus, internal adoption is typically less than complete after initial adoption, as is found in Battisti and Stoneman (2003). The other statistics indicate a wide dispersion of use. Dispersion is higher relative to the mean for less adopted portfolios.

Table 5

Descriptive statistics for intra-firm use of pest control portfolios based on sums of adoptions of component technologies

Portfolio	Mean	Median	StDev	Skewness	Min	Max
Intracrop	1.56	1	1.38	0.95	0	6
	26%		23%		0%	100%
Chemical	3.94	4	1.91	-0.36	0	7
	56%		27%		0%	100%
Extracrop	1.4	1	1.04	0.21	0	3
	47%		35%		0%	100%
Weed	2.67	3	1.17	-0.71	0	4
	67%		29%		0%	100%

Percentages below the statistics are the statistics divided by the total number of technologies in the portfolio.

As an alternative method of intra-firm use, we could perform factor analyses on the portfolios and construct linear measures of adoption from the components that explain most of the variation in the data (Battisti and Iona, 2009). This approach would have advantages and disadvantages. It would recognise the different technological values between portfolios and synergies in adoption, as revealed by variation in adoption preferences. However, interpretations would be made less clear by the overlap between the intra-crop bio-controller and chemical user portfolios. Furthermore, between-portfolio variation is allowed by the method but variation within-portfolio is not permitted, and we are unsure whether such constraints are valid.

We additionally extract survey data on information sources for the farmers. The survey asks what sources farmers use for anything related to farm management in general, and presents various options shown in Table 6. For each source, farmers respond either never (coded as one), rarely (coded as two), occasionally (three), or frequently (four).

Table 6

Farmer information sources and abbreviations

Independent crop consultants (ICC)
Land agents or similar professional persons (AGENTS)
University / academic researchers (ACADEME)
Suppliers (of seed, equipment, chemicals, …) (SUPPLIER)
Buyers (e.g. supermarkets, bread-makers, …) (BUYERS)
Other farmers (FARMERS)
DEFRA publications and/or website (DEFRA)
http://www.voluntaryinitiative.org.uk/ (VIWEB)
Farmers Weekly (FWEEKLY)
Farmers Guardian (FGUARD)
Other

We reduce the measures of information use to two levels, zero and one. The use measure equals zero if the source usage is coded as "never" or "rarely", and one if it is coded as "occasionally" or "frequently". Table 7 summarises the use for each information source. There is considerable variation in the rates of use across sources. The sources with the lowest rates of use are academics (26 percent) and the Voluntary Initiative website (31 percent). The most consulted sources are suppliers (82 percent) and independent crop consultants (80 percent). Buyers are less consulted (37 percent), and other farmers are often used (70 percent) as is government (64 percent). Reliance on agricultural magazines is mixed (65 percent and 37 percent for Farmers Weekly and Farmers Guardian respectively), while about half of farmers use information from land agents and other professionals.

Table 7

Numbers of farmers who use information sources occasionally or frequently

Source	Not used	Used	Total	Use rate
ICC	106	416	522	80%
Agents	279	243	522	47%
Academe	385	137	522	26%
Supplier	96	426	522	82%
Buyers	331	191	522	37%
Farmers	158	364	522	70%
DEFRA	189	333	522	64%
VIweb	361	161	522	31%
FWeekly	181	341	522	65%
FGuard	331	191	522	37%

We also use various questions from the data to construct ancillary determinants for our equations. These are both discrete and continuous variables. They are described in Table 8 and are separated into general data and data on pesticide use, in preparation for their later econometric use.

Table 8

Adoption and use determinants other than general information sources

General data

Arable farming dummy, Livestock farming dummy, Total agricultural area farmed in hectares, Wheat grown dummy, Barley grown dummy, Other cereal grown dummy, Other combinable crop grown dummy, Conventional crop cultivation dummy, Organic crop cultivation dummy, Area sprayed for barley yellow dwarf virus, Area sprayed for autumn OSR, Area sprayed for spring aphids, Area sprayed for orange blossom midge, Area sprayed for summer OSR, Importance of environmental safety for a new pest management strategy, Dummy if the most negative thing about pesticide is it increases costs, Dummy if the most negative thing about pesticide is it kills non target species, Dummy if the most negative thing about pesticide is it contaminates the environment, Dummy if the most negative thing about pesticide is it has possible health risks, Tenant farmer dummy, Full time farming dummy, Part time farming dummy, Sex, Years of farm experience, Formal education, Participation in the Countryside Stewardship Scheme, Participation in entry level Stewardship, Participation in higher level Stewardship, Participation in the Organic Farming Scheme, Participation in the Environmentally Sensitive Areas Scheme, Participation in the Voluntary Agreement on Pesticides Scheme, Participation in the Single Farm Payments Scheme, Crops contracted with buyers dummy

Data on the most important source of pesticide advice

Dummy for an independent adviser / agronomist, Dummy for a decision support system, Dummy for another farmer who is applying pesticides, Dummy for government advice, Dummy for a pesticide salesperson who recommends action, Dummy for another source (The omitted reference is own experience / observations)

4. Estimation procedure

In this section we describe our estimation procedure. Our theory proposes which sources of information will be associated with inter-firm and intra-firm adoption. There are a number of considerations that guide our empirical formulation and estimation. Firstly, it is likely that common included and omitted factors will influence both information use and technology choice. We therefore adopt a system of equations allowing for shared covariates and correlated error terms. Secondly, the direct effects of information on technology choice are of interest, not just the indirect effect of shared influences. Thus, information should enter as a recursive determinant in the technology choice equations, as in Genius et al (2006) who use a trivariate ordered probit. As information is correlated with the technology error term through the correlation with the error term in its own use equation, it is endogenous in the adoption equation. Greene (2008, p823) shows that in the case of a recursive bivariate probit model, the endogeneity can be ignored in maximum likelihood estimation. An alternative to obtain parameter consistency would be use a two step procedure (as in Koundouri et al (2006)). In the case of a bivariate probit-linear model with an endogenous variable, the well known Heckman correction can be applied to the second step of a treatment model (Greene, 2008 p.886f and p.889f). A third consideration in estimation is the number of parameters to be estimated. A system in which use of each information variable is simultaneously determined would proliferate parameters. One solution to this problem is to consider aggregates of information sources as is common in the literature (Genius, 2006; Wozniak, 1993; Wozniak, 1987). However, as we wish to determine the effect of individual sources, this approach is not followed here. A related consideration also concerns feasibility of identification and estimation. The data allows for ordering of use and adoption. A multivariate ordered system would again have many parameters and it is also unclear if variable endogeneity can be ignored as in the bivariate probit model.

Given these considerations, we adopt two broad approaches. One is to estimate linear models containing all information variables as determinants and neglecting their endogeneity (as in Wozniak (1987)). This approach makes allowance for their simultaneous effect. The other approach is to treat the individual information sources as endogenous in bivariate systems with technology adoption as the other determined variable. For the inter-firm model, a bivariate probit is used with information endogenous in the technology adoption equation. For the intra-firm model, a probit-linear model is used with technology as a treatment effect and a Heckman correction.

Influences on inter-firm adoption are tested through the following equations for technology adoption

$$z_1 = x_1'\beta_1 + i'\gamma + \varepsilon_1, \quad t = 1 \quad \text{if } z_1 > 0 \text{ and 0 otherwise,} \tag{1}$$

where z_1 is a latent variable, x_1 is a column vector of non-information determinants of technology adoption, i is a column vector of dummies equal to one for each information source used and zero otherwise, β_1 and γ are column vectors of coefficients with the same dimensions as x_1 and i respectively, ε_1 is a standard normal error term, and t is a dummy for inter-firm adoption for one of the technology portfolios.

We initially estimate equations (1) assuming that the determinant variables are all exogenous. We then introduce an information adoption equation

$$z_2 = x_2'\beta_2 + \varepsilon_2, \qquad i = 1 \quad \text{if } z_2 > 0 \text{ and 0 otherwise} \tag{2}$$

where x_2 is a vector of determinants that may overlap with x_1, β_1 is its coefficient vector, and ε_2 is an error term. ε_1 and ε_2 are bivariate normal with zero means and a covariance matrix $\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$. We further constrain the i and γ vectors to be one dimensional. The models are estimated by maximum likelihood.

The effects of information sources on intra-firm diffusion are tested using a linear model of technology adoption

$$T = x_1'\beta_1 + i'\gamma + \varepsilon_1 \tag{3}$$

where T is a measure of intra-firm adoption for one of the portfolios. x_1, i, β_1, and γ are the same as for equation (1), and ε_1 is a zero mean error term. Initial estimation is by OLS assuming determinant endogeneity. We then introduce the information use equation which is the same as equation (2) and in the parametric constraint, except for the joint distribution of the error terms. Now ε_1 and ε_2 are bivariate normal with zero means and a covariance matrix $\begin{pmatrix} 1 & \rho \\ \rho & \sigma \end{pmatrix}$. The model is estimated by full information maximum likelihood.

The set x_1 of non-information determinants of technology adoption is taken to be the general data variables in Table 8, while the set of determinants of general information usage is taken to be the pesticide information variables in the table. Our reasoning for the latter choice is that pesticide information will have a much greater influence on the choice of general information sources than on organic technology adoption.

Our STATA code is to appear at our website with the next draft of this paper. The data used cannot be provided as its dissemination is restricted; nevertheless it is freely available to researchers at the UK Data Service website[2].

5. Empirical results

Table 9 shows estimated coefficients for the inter-firm technology adoption under the assumption of determinant exogeneity, and Table 10 shows the marginal effects. We comment on the latter.

For the intra-crop bio-controller portfolio, academic information has a large and significantly significant effect on adoption. The effect is moderately large and less significant for independent crop consultant and supplier information, and less for buyer information with ten percent significance. All of these information sources increase adoption. The strongest effects are due to reliable or supply side information sources.

The chemical user portfolio estimates are shown in the next column. Independent crop consultants have a moderately sized and highly significant positive effect on technology adoption. Agents have a smaller, moderately significant negative effect, while suppliers also have a small, but weakly significant and negative, impact.

The third column has coefficients for informational influences on adoption by extra-crop bio-controllers. Agent information has moderate positive economic and statistical effects on technology adoption. The agricultural magazine Farmers Weekly has a similar, but negative effect.

Coefficients for influential information sources on weed focussed farmers are shown in the final column. Academics have an economically small and weakly significant negative effect on adoption. Farmer information has a similar, but positive effect. Information from the Voluntary Initiative website is associated with a moderately large, five percent significant effect.

In summary, we do find evidence for reliable, supply side information having an effect on adoption.

[2] http://www.ukdataservice.ac.uk/

Table 9

Estimated coefficients on information variables for inter-firm diffusion with determinants taken as exogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	0.33**	0.65***	0.17	0.23
	0.16	0.24	0.16	0.2
Agents	0.12	-0.5**	0.31**	-0.18
	0.14	0.24	0.15	0.2
Academe	0.51***	0.23	-0.19	-0.42*
	0.17	0.29	0.16	0.22
Supplier	0.35**	0.46*	0.23	0.15
	0.17	0.26	0.18	0.22
Buyers	0.27*	0.36	-0.07	0.33
	0.15	0.29	0.15	0.22
Farmers	-0.04	0.1	0.14	0.34*
	0.15	0.23	0.16	0.2
DEFRA	0	0.23	0.2	0.06
	0.15	0.23	0.15	0.19
VIweb	0.27	0.19	0.23	0.7**
	0.18	0.32	0.18	0.28
FWeekly	-0.06	-0.38	-0.36**	-0.15
	0.15	0.24	0.16	0.2
FGuard	-0.08	0.13	-0.04	0.17
	0.14	0.24	0.15	0.2
Pseudo R^2	0.24	0.46	0.24	0.3

Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 10

Estimated marginal effects on information variables for inter-firm diffusion with determinants taken as exogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	0.09**	0.07***	0.04	0.03
	0.04	0.02	0.04	0.03
Agents	0.03	-0.05**	0.08**	-0.02
	0.04	0.02	0.04	0.03
Academe	0.13***	0.02	-0.05	-0.06*
	0.04	0.03	0.04	0.03
Supplier	0.09**	0.05*	0.06	0.02
	0.04	0.03	0.05	0.03
Buyers	0.07*	0.04	-0.02	0.05
	0.04	0.03	0.04	0.03
Farmers	-0.01	0.01	0.04	0.05*
	0.04	0.02	0.04	0.03
DEFRA	0	0.02	0.05	0.01
	0.04	0.02	0.04	0.03
VIweb	0.07	0.02	0.06	0.1**
	0.05	0.03	0.04	0.04
FWeekly	-0.01	-0.04	-0.09**	-0.02
	0.04	0.03	0.04	0.03
FGuard	-0.02	0.01	-0.01	0.02
	0.04	0.02	0.04	0.03

Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

In Table 11 we see estimated information coefficients for inter-firm diffusion when the determinants are taken as endogenous, and the marginal effects are in Table 12. The first column in Table 12 shows the marginal effects on adoption in the intra-crop bio-controller portfolio. Independent crop consultants have a moderately positive, and highly significant effect on adoption. The effect of agents is similar. Academics have a large, positive, and highly significant effect on adoption. Suppliers have little effect. Buyer information has a large, positive, and highly significant effect on adoption, as does the Voluntary Initiative website. Information from the

Farmers Guardian is associated with a small and positive increase in adoption, at one percent significance.

The effect of information sources on chemical user adoption is shown in the second column. Independent crop consultants have a small but highly significant positive effect. Agent information has a similar but negative effect, while suppliers have a very small, negative, and one percent significant effect. The effect of farmer information is the same. Information from DEFRA has a small and weakly significant positive effect. Both the Farmers Weekly and Farmers Guardian print publications reduce adoption slightly, with one percent significance.

The third column shows information's effect on adoption in the extra-crop bio-controller portfolio. Agents have a moderately large and highly significant positive effect. DEFRA information has a smaller positive effect, which is also highly significant, and the Voluntary Initiative website impact is the same. Information from Farmers Weekly moderately reduces adoption at one percent significance, while Farmers Guardian information increases it moderately with five percent significance.

Column four shows coefficients for information's influence on weed-focussed adoption. Independent crop consultants have a small, positive effect that is one percent significance. A very small, highly significant reduction in adoption is due to use of agent information, and a slightly larger reduction with five percent significance is attributable to academic information. Farmers have a small, positive, highly significant influence, as does DEFRA. The Voluntary Initiative website is associated with a moderate economical and statistical positive effect, while Farmers Weekly has a weak negative effect.

In summary, we have again found evidence that reliable, accessible information increases inter-firm adoption.

Table 11

Estimated coefficients on information variables for inter-firm diffusion with determinants taken as endogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	0.87**	0.79	1.18***	0.27
	0.36	0.57	0.31	0.44
Agents	1.65***	1.49***	1.52***	1*
	0.09	0.14	0.19	0.56
Academe	1.89***	1.28**	-1.18**	0.63
	0.12	0.6	0.53	0.51
Supplier	1.95***	2.02***	-0.95***	1.58***
	0.1	0.31	0.35	0.47
Buyers	1.73***	1.83***	1.32***	1.75***
	0.1	0.28	0.21	0.25
Farmers	1.7***	1.76***	1.83***	1.17
	0.08	0.26	0.09	0.72
DEFRA	1.49***	1.24**	1.29***	0.72
	0.26	0.49	0.39	0.56
VIweb	1.77***	1.87***	0.97*	1.59***
	0.12	0.21	0.56	0.38
FWeekly	1.63***	1.4***	1.3***	1.22**
	0.09	0.34	0.27	0.6
FGuard	1.5***	1.75***	1.5***	1.75***
	0.08	0.14	0.09	0.12

Coefficients shown are for estimations with a single information source shown in the left column, and are stacked by column. Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 12

Estimated marginal effects on information variables for inter-firm diffusion with determinants taken as endogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	0.08***	0.04***	-0.01	0.03***
	0.03	0.02	0.02	0.01
Agents	0.1***	-0.04***	0.1***	-0.01***
	0.03	0.02	0.02	0
Academe	0.21***	0.02	-0.01	-0.03**
	0.03	0.01	0.03	0.01
Supplier	-0.04	-0.01***	0.09	0
	0.09	0	0.05	0.01
Buyers	0.16***	0.01	0.01	0.04
	0.03	0.02	0.01	0.03
Farmers	0.02	-0.01***	0.08	0.06***
	0.06	0	0.06	0.01
DEFRA	0.03	0.02*	0.06***	0.03***
	0.03	0.01	0.02	0.01
VIweb	0.17***	-0.02	0.06***	0.07**
	0.03	0.01	0.02	0.03
FWeekly	-0.01	-0.03***	-0.09***	-0.01*
	0.05	0.01	0.02	0.01
FGuard	0.05***	-0.04***	0.05**	0.01
	0.02	0.01	0.02	0.05

Coefficients shown are for estimations with a single information source shown in the left column, and are stacked by column. Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 13 shows estimated coefficients for information's influence on intra-firm diffusion when information is taken as exogenous. In the first column, we see that independent crop consultants have a moderate economic and statistical positive effect. Buyers have a larger effect with the same significance. No other variables are significant.

Column two shows results for the chemical user portfolio. Independent crop consultants have a large, positive effect on adoption with five percent significance. Academic information has a larger effect at the same significance, while supplier information has a large positive effect that is weakly significant. Buyer information has big positive effect at one percent significance. DEFRA's impact is large, positive, and moderately significant, as is the impact of the Voluntary Initiative website.

Results for extra-crop bio-controllers are shown in the third column. Independent crop consultants have a moderately positive, weakly significant effect on adoption, with a similar, but negative effect for farmer information. The same effect as for consultants is seen for Voluntary Initiative website and Farmers Guardian newspaper.

Column four shows adoption influence for the weed-focussed farmer portfolio. Buyers have a large positive economic and statistical influence. A moderately positive effect significant at ten percent is due to DEFRA information, with a similar size effect due to the Voluntary Initiative website and Farmers Guardian newspaper, both at ten percent significance.

To summarise, the results here broadly support our claim that intra-firm adoption will be influenced by technical information.

Table 13

Estimated coefficients on information variables for intra-firm diffusion with determinants taken as exogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	0.12**	0.18**	0.08*	0.06
	0.06	0.07	0.04	0.05
Agents	0.07	-0.04	0.04	0.04
	0.07	0.08	0.05	0.06
Academe	-0.02	0.23**	-0.01	-0.02
	0.07	0.09	0.05	0.06
Supplier	0.06	0.16*	0.04	0
	0.07	0.09	0.05	0.06
Buyers	0.14**	0.26***	-0.02	0.23***
	0.06	0.08	0.05	0.05
Farmers	-0.1	-0.08	-0.08*	-0.06
	0.07	0.08	0.05	0.06
DEFRA	0.08	0.2**	0.03	0.11*
	0.07	0.08	0.05	0.06
VIweb	0.08	0.17**	0.08*	0.13**
	0.07	0.09	0.05	0.06
FWeekly	-0.01	-0.11	-0.05	-0.05
	0.06	0.07	0.04	0.05
FGuard	0.07	0.05	0.08*	0.1**
	0.05	0.07	0.04	0.05
R^2	0.18	0.41	0.23	0.27

Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 14 presents estimated coefficients for information sources' effects on intra-firm diffusion when information is taken to be endogenous. Marginal effects are shown in Table 15, and we comment on them. The first column in Table 15 shows coefficients for information's influence on adoption of the intra-crop portfolio. Independent crop consultants have a large positive effect on adoption, with five percent significance. Buyers also have a large positive impact on adoption, with weak significance. Similarly large positive impacts with five percent significance are due to information from DEFRA and the Voluntary Initiative website.

Column two shows results for the chemical user portfolio. Adoption is substantially increased by academic information with high significance, with similar findings for information from suppliers, buyers, DEFRA, and the Voluntary Initiative website.

The next column presents the findings for the extra-crop bio-controller portfolio. Independent crop consultants have a large, moderately significant positive effect on adoption, while the Farmers Weekly is associated with a similar but negative effect on adoption.

Column four presents coefficients for information's effect on weed-focussed portfolio adoption. Buyer information has a large, positive, and highly significant effect on adoption. The same is true for information from DEFRA, the Voluntary Initiative website, and the Farmers Guardian.

In summary, the estimates support our theoretical finding that technical information sources will be influential on intra-firm adoption.

Table 14

Estimated coefficients on information variables for intra-firm diffusion with determinants taken as endogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	1.06***	2.19***	0.6***	0.46
	0.26	0.49	0.23	0.33
Agents	2.73***	3.58***	1.21***	1.12**
	0.22	0.33	0.33	0.45
Academe	2.73***	3.08***	1.35***	0.95**
	0.15	0.42	0.3	0.38
Supplier	0.64	3.18***	-0.36	1.62***
	0.41	0.37	0.6	0.38
Buyers	2.62***	3.62***	1.88***	2.61***
	0.2	0.35	0.19	0.39
Farmers	0.91*	3.09***	0.68	1.92***
	0.52	0.39	0.44	0.33
DEFRA	1.91***	3.14***	0.87**	1.84***
	0.31	0.4	0.39	0.49
VIweb	2.49***	2.96***	1.55***	1.4***
	0.2	0.38	0.28	0.32
FWeekly	1.59***	2.95***	0.53	1.94***
	0.33	0.32	0.33	0.3
FGuard	2.41***	3.12***	1.53***	1.44***
	0.22	0.37	0.3	0.44

Coefficients shown are for estimations with a single information source shown in the left column, and are stacked by column. Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 15

Estimated marginal effects on information variables for intra-firm diffusion with determinants taken as endogenous

	Intracrop	Chemical	Extracrop	Weed
ICC	0.27**	0.27	0.24**	0.19
	0.12	0.19	0.11	0.14
Agents	0.17	0.11	0.12	0.14
	0.12	0.16	0.09	0.11
Academe	0.08	0.66***	-0.02	0.1
	0.11	0.16	0.1	0.14
Supplier	0.13	0.51***	0.15	0.18
	0.16	0.2	0.11	0.16
Buyers	0.2*	0.66***	-0.1	0.43***
	0.12	0.16	0.08	0.11
Farmers	-0.05	0.17	-0.05	0.12
	0.12	0.15	0.09	0.11
DEFRA	0.23**	0.55***	0.12	0.3***
	0.11	0.16	0.09	0.11
VIweb	0.32**	0.72***	0.16	0.58***
	0.15	0.22	0.12	0.12
FWeekly	-0.09	-0.23	-0.22**	-0.15
	0.13	0.16	0.09	0.11
FGuard	0.08	0.15	0.13	0.34***
	0.12	0.16	0.09	0.11

Coefficients shown are for estimations with a single information source shown in the left column, and are stacked by column. Standard errors are shown below the coefficients. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

We summarise our findings compared with our expectations in Table 16. The observed column is constructed by counting significance stars on the marginal effects in the inter-firm and intra-firm tables, and summing across the exogenous and endogenous totals for each diffusion type. There is broad agreement with our expected results. Sources that provide information on technological feasibility that may be used without much expense are found to influence inter-firm adoption, while sources of more detailed technological information that probably require more processing effort are revealed to influence intra-firm adoption.

Table 16

Sources of information, the expected types of diffusion that they influence, and the diffusion types they are empirically found to influence

Source	Expected	Observed
ICC	Both	Both
Agents	Both / inter	Inter
Academe	Both	Both / inter
Supplier	Inter	Inter (weak effect)
Buyers	Intra	Intra
Farmers	Inter	Inter
DEFRA	Both	Both
VIweb	Both	Both
FWeekly	Inter	Inter
FGuard	Inter	Inter / both

6. Conclusions

We have presented a model of the effect of information sources on inter-firm and intra-firm diffusion and tested it with UK farming data. Consistent with our model, we found evidence that inter-firm adoption is often driven by reliable and accessible information, while intra-firm adoption is often driven by technical information.

We find that information from farmers affects inter-firm adoption, but not intra-firm adoption. The result contrasts with Conley and Udry (2010)'s finding that such information adjusts the intra-farm level of adoption in Ghanaian pineapple growers. They find close response by farmers to communication within the farmers' information neighbourhoods, so it is unlikely that farmer information is just proxying for other forms of information that we have included but that they exclude. It is possible that different forms of information are suitable in Ghana for reasons omitted from our model. Verbal communication may be relatively ineffective for transfer of UK intra-firm farming information, or Ghanaians may be more willing to share information. Alternatively, as an extension to our model, Ghanaian farmer information may be more suitable for analytical processing than UK farmer information. Baerenklau (2005) looks at US farmers and finds that neighbourhood effects are not significant in their intra-firm adoption of new types of forage grasses, so conceivably the difference can be generalised to farmers in developing and developed countries.

Our theoretical and empirical models could be investigated further. The relative role of education in inter-firm and intra-firm diffusion could be assessed, and the comparative importance of economic and information determinants. The disclosure value associated with intra-firm diffusion could be examined, and the extent to which influences on inter-firm and intra-firm adoption cross-over to each other. The extent to which information changes technology's effect on profitability could be examined.

We have lost some statistical content in forming dummies for informational use and technological adoption. We could investigate alternative econometric models in which the ordering of the original data is retained. As noted previously, the retention will create challenges in estimation for reasons of identification and consistency.

Our work has a number of policy implications. One is that information encouraging initial adoption without support for detailed implementation is not likely to promote full technological use. Another implication is that government information has a role in both inter-firm and intra-firm diffusion, although whether it is cost-effective is another issue. A further implication is that although UK farmers have some role in inter-firm adoption, their role in intra-firm adoption is not significant so network construction will not necessarily lead to much fuller diffusion.

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