Four papers on the economics of technology

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Introduction

This dissertation consists of four chapters on the economics of technology. The chapters study different aspects of innovation generation and diffusion. In broad terms, chapter one looks at how innovation spreads by social contact, while chapter two looks at welfare consequences of diffusion. Chapter three examines how information sources affect diffusion, and chapter four looks at the relation of finance with innovation generation.

The first chapter empirically investigates the dynamics of the marginal propensity to pirate for computer software. We introduce a state space formulation that allows us to estimate error structures and parameter significance, in contrast to previous work. For data from 1987-92, we find a rising propensity to pirate as the number of existing pirate copies increases, and higher late piracy incidence than implied by static models. We strengthen prior results on the impact of piracy in the spreadsheet market, finding it to be the only significant internal influence on diffusion. However, when we allow for negative error correlation between legal and pirate acquisitions, we contradict earlier work by finding that, in the word processor market, piracy did not contribute to diffusion and only eroded legal sales.

The second chapter is a paper forthcoming in the European Journal of Operational Research[1]. We present an information good pricing model with persistently heterogeneous consumers and a rising marginal propensity for them to pirate. The dynamic pricing problem faced by a legal seller is solved using a flexible numerical procedure with demand discretisation and sales tracking. Three offsetting pricing mechanisms occur: skimming, compressing price changes, and delaying product launch. A novel trade-off in piracy's effect on welfare is identified. We find that piracy quickens sales times and raises welfare in fixed size markets, and

[1] Waters, J., 2014. Welfare implications of piracy with dynamic pricing and heterogeneous consumers. European Journal of Operational Research, In press.

does the opposite in growing markets. In our model, consumers benefit from very high rates of piracy, legal sellers always dislike it, and pirate providers like moderate but not very high rates.

In the third chapter, we study the effect of different information sources on technology adoption between and within companies. Our model of economically optimising companies predicts that initial adoption will be primarily affected by information that reduces uncertainty about a technology's performance, while intensification of intra-firm use will be mainly influenced by information that increases income from the technology. The theory is tested on data describing adoption of organic farming techniques by UK farmers. Our predictions are broadly supported by the empirical results. Information from land agents, farmers, and newspapers mainly influences initial adoption, from academia and government largely influences intensification, and from crop consultants, suppliers, and buyers influences both.

Financing innovation presents informational and control problems for the financier, and different solutions are used for funding of US companies and universities. In the fourth chapter, we examine how funding characteristics influenced the change in innovation during the 2007-8 financial crisis for both. We extend prior theories of external financing's effect on company performance during crises, firstly to university performance, and secondly to show the influence of time variation in aggregate funding. Empirical results are consistent with our theory: external dependence and asset intangibility had a limited effect on company innovation on entering the crisis, but increased university innovation.

We do not describe here the limitations and gaps of the studies, and proposals for future work. Instead, they are addressed in the conclusions of each chapter.

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Computer code

All code used in the text is on the USB flash drive provided with the dissertation submission. All data is provided as well, except for the farming data used in chapter three, which is under restricted access from the data supplier. If reviewers would like to see it, please contact me.

Chapter 1

Variable marginal propensities to pirate and the diffusion of computer software

1.1 Introduction

Social contact has long been implicated in technology diffusion, following Bass (1969). The idea is that existing users of a technology influence non-users to adopt the technology. Similar mechanisms have been proposed for describing markets subject to software piracy, the illegal copying of software. In pirate diffusion literature including Givon *et al.* (1995), Prasad and Mahajan (2003), and Liu *et al.* (2011), influenced non-users may acquire the legal or pirated good. Owners of the pirated good may influence non-users, like legal owners.

The pirate diffusion literature presents a variety of reasons why piracy may be beneficial to legal sellers and consumers. In Givon *et al.* (1995) and Givon *et al.* (1997) it is suggested that pirate acquisitions may accelerate legal diffusion through pirate owners' social contacts with non-users. Prasad and Mahajan (2003) show that legal profits may be increased for the same reason, when piracy rates are subject to control by the legal sellers and sales affect price preferences of remaining non-users in a specific way. Liu *et al.* (2011) propose a similar mechanism, where either piracy or pricing can be selected as routes to obtain optimal diffusion speed prior to mature market sales.

The marginal propensity to pirate is the proportion of pirate acquisitions out of total new acquisitions. Its value and dynamics are critical influences on whether piracy does indeed benefit legal sellers. If the marginal propensity to pirate rises as the market size increases, then legal sellers will capture little of the late market. If they then take measures to avoid piracy, consumer welfare is likely to be affected.

Despite the importance of the marginal propensity to pirate, we are unaware of any pirate diffusion studies that test whether it rises or falls with diffusion. Much pirate diffusion research has been theoretical. The empirical work by Givon *et al.* (1995) and Givon *et al.* (1997) assumes that the marginal propensity to pirate is constant. In Haruvy *et al.* (2004), the ratio of pirate sales to legal sales can fall at a constant exponential rate as the number of users increases. However, the interpretation of the rate in terms of piracy protection and resulting company optimisation function precludes the possibility of an increasing ratio.

There are reasons to believe that increased diffusion could lower or raise the share of piracy in acquisitions. For example, on one hand legal sellers may find it cost-effective to take action against piracy only when it reaches a certain level, so increased piracy could lower the marginal propensity to pirate. On the other hand, widespread piracy may make new piracy less difficult and more socially acceptable, so that the marginal propensity to pirate would rise with higher piracy prevalence.

In this paper, we estimate the level and change in the marginal propensity to pirate for data on spreadsheets and word processors. The statistical significance of the parameters and the models' predictive power is assessed.

We compare diffusion when we allow for variable marginal propensity to pirate to diffusion without it.

Our theoretical model is a small modification of that in Givon *et al.* (1995). It introduces an adjustment factor to pirate sales, where the factor is the number of users of pirate goods raised to an estimated coefficient. The adjustment represents the effect of factors promoting or hindering piracy. We also consider an alternative modification where past piracy explicitly adjusts piracy's share of sales.

The stochastic component of the model includes errors in the legal and pirate acquisitions, and allows for their correlation. In order to achieve identification, we restrict the error matrix to depend on a single parameter. However, we consider multiple forms for the error, including positive and negative correlation and heterogeneity.

We use data on legal software sales taken from Givon *et al.* (1995), which is also used in Haruvy *et al.* (2004) and (for calibration) in Liu *et al.* (2011). As with these prior authors, we have no piracy data. Givon *et al.* (1995) estimate their model by non-linear least squares while omitting joint error specifications between the legal and pirate data, and so do not report parameter standard errors. Standard errors are also missing from non-linear least squares estimates in Givon *et al.* (1997), simulated annealing estimates in Haruvy *et al.* (2004), and calibrated model solutions in Liu *et al.* (2011).

We estimate our model by formulating it in state space form, with pirate acquisitions as an unobserved state variable. We calculate one-step ahead predictions using the Kalman filter, and maximise the resulting likelihood to give parameter estimates. We allow for cross-sectional relations between legal and pirate diffusion, and present parameter standard deviations unlike prior work. We use the continuous time, discrete observation extended

Kalman filter to avoid time interval bias, in common with Xie *et al.* (1997). However, whereas they use the filter projection as a Bayesian updating procedure for parameter estimates and sales simultaneously, we leave the parameters outside the state variable, and so make them available for classical estimation. As extensive piracy represents a hidden phenomenon of uncertain impact, limiting the impact of prior beliefs is a prudent approach to analysis and permits classical inference.

Our central estimates show that the share of pirate acquisitions out of current acquisitions rose with past piracy. The expanded specification offers gains in fit and assumption plausibility that are robust across different deterministic and stochastic specifications, but frequently lack parameter certainty. Predictive performance is mixed. We find dynamic estimates of piracy that are higher than static estimates at long time scales.

Givon *et al.* (1995) find that past piracy is an important internal influence on spreadsheet diffusion. We strengthen their result, finding that piracy was the only economically and statistically significant internal influence on spreadsheet diffusion, with no role for past legal sales. Our finding is consistent across all specifications. Givon *et al.* (1995) also find that piracy influenced word processor diffusion. In many specifications we obtain similar results. However, when we allow for negative correlation between legal and pirate errors, piracy is a negligible influence on diffusion and only serves to displace legal sales. The negative correlation stochastic specification outperforms models with no correlation, and is our preferred specification. We interpret the difference between the results on piracy's effect as being due to stochastic correlations being incorrectly ascribed to deterministic links when no correlations are allowed.

In section 1.2 we present our model and in section 1.3 we look at the data and empirical method. Results are in section 1.4 and section 1.5 concludes.

1.2 Model

In this section we present our model of diffusion with increasing marginal propensity to pirate. The model is a small deterministic variation on the one described in Givon *et al.* (1995), and a larger stochastic variation. It describes the joint evolution of a technology's acquisition by legal and pirate means. The deterministic component is similar to a bivariate Bass model in that either source or an external advertiser can inform a non-user about the technology, who then adopts. The stochastic specification allows for correlation in the adoptions by either route.

There is a population of agents of constant size m who are able to buy a computer. The adoption process for computers follows a standard univariate Bass model. At any time, some of the population will have acquired a computer, and the rest will not yet have bought one and remain potential buyers. Initially, there are no owners. The potential users are subject to external advertising, so that a fixed proportion p of them are contacted by advertisers and then buy the computer in any time period. There is also a word-of-mouth effect by which an additional share of potential adopters adopts in the period, where the share is proportional to the number of previous adopters with constant of proportionality equal to q/m. The diffusion pattern for computers thus follows the differential equation

$$dN_t/dt = (p + q\frac{N_t}{m})(m - N_t) \tag{1.1}$$

An agent can acquire a computer software product only if they own a computer. Of the computer owning population, a number Z_t of these potential software users will have acquired the software and the remainder totalling $N_t - Z_t$ will not yet have acquired it. They can acquire it only once. Initially there are no computer software users. The software can be produced as a legal or pirate copy. The number of legal owners is X_t and the number of pirate owners is Y_t, so $X_t + Y_t = Z_t$.

Non-users are subject to external influence so that they acquire legal copies at an instantaneous rate of a. They are also subject to internal influences from current legal and pirate owners. Legal owners influence them to acquire either legal or pirate copies at a rate that is linear in the number of legal owners, $b_1 X_t / N_t$. Pirate owners influence them to acquire software by either route at a rate linear in the number of pirate owners, $b_2 Y_t / N_t$. For non-users who are internally influenced to acquire the software, a share α acquires the legal good, while the remaining $1 - \alpha$ intend to acquire a pirate copy. These number of these motivated non-users who adopt the pirate copy is then either magnified or diminished by the number of existing pirate copies. For example, it may be magnified if current pirates make piracy more acceptable, or diminished if increased piracy leads to anti-piracy measures being taken. The magnification or diminution is represented by a multiplier applied to the number of pirate adopters, $\max(Y_{t-1}, 1)^{\varepsilon}$, depending on whether ε is greater or less than zero. Givon *et al.* (1995) constrain $\varepsilon = 0$.

Thus, we have the following model

$$
\begin{aligned}
dX_t &= (\left[a + \alpha \frac{b_1 X_t + b_2 Y_t}{N_t} \right] (N_t - X_t - Y_t))dt + dw_1 \\
dY_t &= (\left[(1-\alpha) \max(Y_t, 1)^{\varepsilon} \frac{b_1 X_t + b_2 Y_t}{N_t} \right] (N_t - X_t - Y_t))dt + dw_2 \qquad (1.2)
\end{aligned}
$$

where $\boldsymbol{dw} = (dw_1, dw_2) \sim N(0, \boldsymbol{Q}dt)$ is a normal error term with covariance matrix $\boldsymbol{Q}dt$. The explicit introduction of general errors and allowance for their covariance is a novelty over the specification in Givon *et al.* (1995), or the sampling errors in Haruvy *et al.* (2004). We consider their structure in the estimation section.

1.3 Estimation

In this section, we describe our empirical approach, presenting the data and estimation method.

1.3.1 Data

The data we use is from Givon *et al.* (1995). It consists of legal sales of personal computers using a DOS operating system, of spreadsheets (which we later abbreviate to S in tables), and of word processors (abbreviated to WP in tables) in the UK, and is reported monthly from January 1987 to August 1992 inclusive. As with Givon *et al.* (1995), we assume that DOS personal computers were introduced in October 1981 and the two software products were introduced in October 1982. These assumptions are used to determine initial values for cumulative sales in January 1987.

1.3.2 Estimation by maximum likelihood

We now present the estimation method for our model and its restriction to the Givon *et al.* (1995) pirate model. It is maximum likelihood estimation with tracking of the likelihood function through an extended Kalman filter. The approach generates estimates of the joint error structure in legal and pirate acquisitions, and parameter standard errors.

1.3.2.1 The extended Kalman filter with continuous state and discrete observations

The extended Kalman filter with continuous state and discrete observations operates on state space models of the form

$$d\boldsymbol{\xi}_{t+1}/dt = f(\boldsymbol{\xi_t}, \boldsymbol{u_t}) + \boldsymbol{v}_{t+1} \tag{1.3}$$

$$\boldsymbol{z_t} = h(\boldsymbol{\xi_t}) + \boldsymbol{w_t} \tag{1.4}$$

where $\boldsymbol{z_t}$ is a vector of variables observed at time t and $\boldsymbol{\xi}_t$ is a state vector of possibly unobserved variables. $\boldsymbol{u_t}$ is a vector of exogenous variables, while f and h are differentiable functions. The error vectors $\boldsymbol{v}_{t+1}$ and $\boldsymbol{u}_{t+1}$ are mutually uncorrelated white noise, with contemporaneous error variances given by $E(\boldsymbol{v_t}\boldsymbol{v_t}^T) = \boldsymbol{Q_t}$ and $E(\boldsymbol{w_t}\boldsymbol{w_t}^T) = \boldsymbol{R}$.

The filter generates repeated linear forecasts based on past data given at discrete intervals, with forecasts generated recursively through a linearised approximation to the continuous generating system. It proceeds by two steps at each period in a time series, alternating between forecasting based on past data and projection based on current data. It tracks the forecasted state variable $\boldsymbol{\xi_t}$ given data available at time $t-1$ (when the forecast is denoted $\boldsymbol{\xi}_{t|t-1}$) and the projected state variable given data available at time t (the projection is denoted $\boldsymbol{\xi}_{t|t}$). The forecast mean squared errors are also tracked. They are denoted $\boldsymbol{P}_{t|t-1} = E((\boldsymbol{\xi_t} - \boldsymbol{\xi}_{t|t-1})(\boldsymbol{\xi_t} - \boldsymbol{\xi}_{t|t-1})^T)$ and $\boldsymbol{P}_{t|t} = E((\boldsymbol{\xi_t} - \boldsymbol{\xi}_{t|t})(\boldsymbol{\xi_t} - \boldsymbol{\xi}_{t|t})^T)$.

In detail, the filter stages are as follows.

Initialisation

Estimates are made of the state vector and its mean squared error matrix in the absence of any information at time zero, that is, of $\boldsymbol{\xi}_{0|0}$ and $\boldsymbol{P}_{0|0}$.

Forecasting

Given $\boldsymbol{\xi}_{t|t}$ and $\boldsymbol{P}_{t|t}$ for any t, we integrate the equations

$$d\boldsymbol{\xi}_t/dt = f(\boldsymbol{\xi_t}, \boldsymbol{u_t}) \tag{1.5}$$

$$d\boldsymbol{P_t}/dt = \boldsymbol{F_t}\boldsymbol{P_t^T} + \boldsymbol{P_t}\boldsymbol{F}^T + \boldsymbol{Q_t} \tag{1.6}$$

where $\boldsymbol{F_t} = df/d\boldsymbol{\xi}^T$ is the Jacobian of f evaluated at $(\boldsymbol{\xi}_t, \boldsymbol{u_t})$. The integration is performed from t to $t+1$, with the initial $\boldsymbol{\xi}_t = \boldsymbol{\xi}_{t|t}$ and $\boldsymbol{P_t} = \boldsymbol{P}_{t|t}$ in the first and second equations respectively. We set $\boldsymbol{\xi}_{t+1|t}$ and $\boldsymbol{P}_{t+1|t}$ to be the integrated values at the corresponding end points. The forecasted value for the observation equation and its MSE are then

$$\boldsymbol{z}_{t+1|t} = \boldsymbol{H}\xi_{t+1|t} \tag{1.7}$$

$$\boldsymbol{MSE}(\boldsymbol{z}_{t+1|t}) = \boldsymbol{H}_{t+1}\boldsymbol{P}_{t+1|t}\boldsymbol{H}_{t+1}^T + \boldsymbol{R}_{t+1} \tag{1.8}$$

where $\boldsymbol{H}_{t+1} = dh/d\boldsymbol{\xi}^T$ is the Jacobian of h evaluated at $\boldsymbol{\xi}_{t+1|t}$.

Updating

Given $\boldsymbol{\xi}_{t+1|t}$ and $\boldsymbol{P}_{t+1|t}$, we update the forecasts with data $\boldsymbol{z}_{t+1}$ at time $t+1$ using the formulae

$$\boldsymbol{\xi}_{t+1|t+1} = \boldsymbol{\xi}_{t+1|t} + \boldsymbol{K}_{t+1}(\boldsymbol{z}_{t+1} - h(\boldsymbol{\xi}_{t+1|t})) \tag{1.9}$$

$$\boldsymbol{P}_{t+1|t+1} = (\boldsymbol{I} - \boldsymbol{K}_{t+1}\boldsymbol{H}_{t+1})\boldsymbol{P}_{t+1|t} \tag{1.10}$$

where $\boldsymbol{I}$ is the identity matrix with dimension equal to the number of state variables, and

$$\boldsymbol{K}_{t+1} = \boldsymbol{P}_{t+1|t}\boldsymbol{H}_{t+1}^{T}(\boldsymbol{H}_{t+1}\boldsymbol{P}_{t+1|t}\boldsymbol{H}_{t+1}^{T} + \boldsymbol{R}_{t+1})^{-1} \tag{1.11}$$

.

1.3.2.2 State space representation of the pirate diffusion model

We may represent our extended pirate diffusion model in equations 1.2 in state space format with the following definitions:

$$\boldsymbol{\xi}_t = \begin{pmatrix} X_t \\ Y_t \end{pmatrix} \tag{1.12}$$

$$f(\boldsymbol{\xi_t}, \boldsymbol{u_t}) = \begin{pmatrix} f_1 \\ f_2 \end{pmatrix} \tag{1.13}$$

$$\boldsymbol{u}_t = 0 \tag{1.14}$$

$$\boldsymbol{F} = \begin{pmatrix} F_{1,1} & F_{1,2} \\ F_{2,1} & F_{2,2} \end{pmatrix} \tag{1.15}$$

$$\boldsymbol{v}_t = \begin{pmatrix} \varepsilon_X \\ \varepsilon_Y \end{pmatrix} \tag{1.16}$$

$$\boldsymbol{z_t} = \begin{pmatrix} X_t \end{pmatrix} \tag{1.17}$$

$$\boldsymbol{h}(\boldsymbol{\xi}_t) = \boldsymbol{\xi}_t \tag{1.18}$$

$$\boldsymbol{H} = \begin{pmatrix} 1 & 0 \end{pmatrix} \tag{1.19}$$

$$\boldsymbol{w_t} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \tag{1.20}$$

where the components of the vector $f(\boldsymbol{\xi_t}, \boldsymbol{u_t})$ are given by

$$f_1 = \left[a + \alpha \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \tag{1.21}$$

$$f_2 = \left[(1-\alpha) \max(Y_{t-1}, 1)^{\varepsilon} \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \tag{1.22}$$

and the components of the matrix $\boldsymbol{F}$ are given by the following expressions:

$$
\begin{aligned}
\boldsymbol{F}_{1,1} =& \alpha b_1 - a - 2\alpha\frac{b_1}{N_t}X_{t-1} - \alpha\frac{b_1+b_2}{N_t}Y_{t-1} && (1.23)\\
\boldsymbol{F}_{1,2} =& \alpha b_2 - a - \alpha\frac{b_1+b_2}{N_t}X_{t-1} - 2\alpha\frac{b_2}{N_t}Y_{t-1} && (1.24)\\
\boldsymbol{F}_{2,1} =& \left[(1-\alpha)\max(Y_{t-1},1)^{\varepsilon}\frac{b_1}{N_t}\right](N_t - X_{t-1} - Y_{t-1})\\
&- \left[(1-\alpha)\max(Y_{t-1},1)^{\varepsilon}\frac{b_1X_{t-1}+b_2Y_{t-1}}{N_t}\right] && (1.25)\\
\boldsymbol{F}_{2,2} =& \left[(1-\alpha)\varepsilon\max(Y_{t-1},1)^{\varepsilon-1}\frac{b_1X_{t-1}+b_2Y_{t-1}}{N_t}\right]\\
&\times (N_t - X_{t-1} - Y_{t-1})\\
&+ \left[(1-\alpha)\max(Y_{t-1},1)^{\varepsilon}\frac{b_2}{N_t}\right](N_t - X_{t-1} - Y_{t-1})\\
&- \left[(1-\alpha)\max(Y_{t-1},1)^{\varepsilon}\frac{b_1X_{t-1}+b_2Y_{t-1}}{N_t}\right] && (1.26)
\end{aligned}
$$

.

The stochastic component of our model includes all sources of error. In contrast, the formulations in Schmittlein and Mahajan (1982) and Basu *et al.* (1995) allocate all error to differences from multinomial sampling of adoption timing. Thus, while both we and these authors use maximum likelihood estimation, we are not susceptible to the type of criticism levelled in Srinivasan and Mason (1986) that our error specification leads to underestimation of errors.

Our general variance-covariance matrix specification allows for contemporaneous correlation only and is given by

$$\boldsymbol{Q_t} = \begin{pmatrix} q_{1,1} & q_{1,2} \\ q_{1,2} & q_{2,2} \end{pmatrix} \tag{1.27}$$

$$\boldsymbol{R_t} = \mathbf{0} \tag{1.28}$$

for scalars $q_{1,1}$, $q_{1,2}$, $q_{2,1}$, and $q_{2,2}$.

We have assumed that the errors occur in the state equation rather than the observation equation, so that errors are persistent over time. This approach is consistent with the accumulating errors used in estimation methods including OLS (Bass, 1969), NLS (Srinivasan and Mason, 1986; Jain and Rao, 1990), and MLE (Schmittlein and Mahajan, 1982; Basu *et al.*, 1995) specifications of the deterministic-stochastic Bass model.

The restriction on the $\boldsymbol{R}$ matrix reduces the number of parameters in our model. State space models are typically underidentified in maximum likelihood estimation (Hamilton, 1994, pp.387-8). To achieve identification, we further restrict the parameters in the $\boldsymbol{Q}$ matrix. Our initial specification sets $q_{1,1} = q_{2,2} = \sigma^2$ for some constant σ^2 and $q_{1,2} = q_{1,2} = 0$. Later, we consider alternative specifications for the fixed parameters.

The initial state vector $\boldsymbol{\xi}_{0|0}$ in January 1987 is generated by iterating on the system in equations 1.2 from October 1982 using the parameters estimated in Givon *et al.* (1995). The initial mean squared error matrix $\boldsymbol{P}_{0|0}$ is assumed to be the zero matrix, so the starting state vector is known with certainty.

For the forecasting stage, we integrate equations 1.5 and 1.6 numerically over ten iterations. We also require estimates of N_t. From equation 1.1, it follows a Bass model. Givon *et al.* (1995) make the same assumption and fit the equation by non-linear least squares. We retain their estimated parameters of $p = 0.00037$, $q = 0.0316$, and $m = 15,386,100$.

1.3.2.3 Maximum likelihood estimation

The one step ahead forecasts for the observation $z_{t+1|t}$ and its mean squared error $MSE(z_{t+1|t})$ are described by equations 1.7 and 1.8. Given a distribution f_{Z_t} of the next observation dependent on these two parameters, we may construct the sample log likelihood as

$$\sum_{t=0}^{T-1} log f_{Z_{t+1}}(z_{t+1}) \tag{1.29}$$

where the distribution $f_{Z_{t+1}}$ is conditioned on $z_{t+1|t}$ and $MSE(z_{t+1|t})$. Under the assumption of normal distributions for $\boldsymbol{\xi}_{0|0}$, v_t, and w_t, the log likelihood is (Hamilton, 1994, p.385)

$$\begin{aligned} log f_{Z_{t+1}}(z_{t+1}) =& (2\pi)^{-n/2} \left| \boldsymbol{H}_{t+1} \boldsymbol{P}_{t+1|t} \boldsymbol{H}_{t+1}^T + \boldsymbol{R}_{t+1} \right|^{-1/2} \\ & \times exp\{-(1/2)(\boldsymbol{z}_{t+1} - H_t \boldsymbol{\xi}_{t+1|t})^T (\boldsymbol{H}_{t+1} \boldsymbol{P}_{t+1|t} \boldsymbol{H}_{t+1}^T + \boldsymbol{R}_{t+1})^{-1} \\ & \times (\boldsymbol{z}_{t+1} - H_t \boldsymbol{\xi}_{t+1|t})\} \end{aligned} \tag{1.30}$$

where $|\boldsymbol{M}|$ is the determinant of $\boldsymbol{M}$ and n is the dimension of w_t.

We maximise the log likelihood function in equation 1.30 numerically. The maximisation has to give estimates in feasible parameter regions, with positive q variance parameters, a, b_1, and b_2 contact parameters that are positive and bounded by unity, and the same for the α share parameter. We further constrain the ε parameter to lie between -0.2 and 0.2, the α parameter to be no larger than 0.02, and $q_{1,1}$ not to exceed 10^9. Estimates are comfortably within these domains, so they restrict the region for checking without excluding probable solutions.

To constrain the variables to lie in the required domains, we map to them by functions whose input variables are unconstrained (see Hamilton (1994, pp.146-8)). The functions are $\phi = 0.2\varepsilon/(1+|\varepsilon|)$, and $\phi = k\lambda^2/(1+\lambda^2)$ with the other parameters replacing λ for appropriate rescaling factors k. We then maximise the transformed functions with respect to the unconstrained variables using a Nelder-Mead algorithm. We start the algorithm from the parameter solutions in Givon *et al.* (1995). The solutions in the transformed parameters give solutions in the original parameters.

The Hessian for the maximised transformed function yields second derivative estimates of the standard errors for the transformed parameters. We can calculate standard error estimates for the original parameters by calculating the Hessian with respect to the non-transformed function. However, a flat likelihood function in a couple of the parameter directions and limits on accuracy for numerically calculated second derivatives meant that negative estimates of variance were occasionally produced in the non-transformed function (but never in the transformed function). So we use variance estimates calculated from the outer product of the score matrix at the original parameter values. The estimates were invariably positive.

The estimation was implemented in the R programming language (R Development Core Team, 2009) using the library packages MASS and numDeriv. We employed the Microsoft Excel add-in Excel2LaTeX to generate the tables. The code is available from the author's website[1].

[1] http://ebasic.easily.co.uk/02E044/05304E/mpp_and_diffusion.html

1.4 Results

In this section we present our results. Subsection 1.4.1 gives estimates for our model and its restriction with constant marginal propensity to pirate, as in Givon *et al.* (1995). Subsection 1.4.2 looks at the model's out of sample performance, subsection 1.4.3 examines estimates with alternative error specifications, and subsection 1.4.4 considers parameter estimates for a qualitatively similar but functionally different model.

1.4.1 Parameter estimates

Table 1.1 shows parameter estimates for our model and its restriction to the Givon *et al.* (1995) model. In column one, our model is fitted to the word processor data. The a parameter equals 0.00146, which is higher than the 0.0002 rate reported in Givon *et al.* (1995). Our rates lie between the mean and median of estimates reported in the meta-analysis of Bass curves in Van den Bulte and Stremersch (2004), whereas the Givon *et al.* (1995) estimate lies at the lower end of their range. Thus, we find that word processors were subject to external influence to a more usual extent than is found in Givon *et al.* (1995) (although the Van den Bulte and Stremersch (2004) data does not disaggregate their reported figure by annual, quarterly, and monthly frequency of calculation, so the sub-divided ranges may move closer to the Givon *et al.* (1995) figure). Thus, we find a higher effect of external influence on diffusion. The b_1 parameter equals 0.109, describing the internal influence on sales by legal owners. The value is lower than in Givon *et al.* (1995) where it is 0.135. Our estimate for the pirate internal influence parameter b_2 is 0.0888, again lower than in Givon *et al.* (1995) at 0.135 too. Our α parameter is 0.163, representing the proportion of internally influenced adopters who buy the legal software when few past pirate copies have been made. It is higher than in Givon *et al.* (1995) (0.144). The σ^2 variance parameter is 10,800,000, giving an implied standard deviation for legal and pirate acquisitions of 3,300 units per month. The ε parameter is 0.0226, indicating that the marginal propensity to pirate rises as the number of pirates rises. This is consistent with a hypothesis that increasing piracy prevalence makes it more viable or acceptable for new adopters to acquire pirate copies. The significance of all parameters is low, except for the error variance.

Table 1.1: Parameter estimates for our pirate model and the $\varepsilon = 0$ restricted model

	WP	WP	S	S
a	0.00146	0.00151	0.00155	0.00148
	0.00463	0.0048	0.00429	0.00262
b_1	0.109	0.229	0.00176	0.00000
	0.798	1.01	0.595	0.341
b_2	0.0888	0.0962	0.0509	0.114 **
	0.356	0.173	0.38	0.0547
α	0.163	0.124 **	0.224	0.101 **
	0.39	0.0596	1.36	0.045
σ^2	0.0108 ***	0.0107 ***	0.00379 ***	0.00403 ***
	0.00202	0.00203	0.000732	0.000756
ε	0.0226		0.0684	
	0.171		0.484	
AIC	1287.0	1285.1	1217.0	1218.8
MSE (%)	100	100	95	100

Standard deviations are shown below the coefficients. *** denotes a p-value of less than 0.01, ** of less than 0.05, * of less than 0.1. MSEs are expressed as percentages of the MSE for the corresponding restricted model. σ^2 is reported in units of 10^9. WP means word processor and S means spreadsheet.

In column two, we set the ε parameter to zero to see how the parameters and fit adjust compared with the model including it. The parameters on

a, b_2, and σ^2 change little, although the significance on b_2 increases whilst remaining low. The b_1 parameter rises to 0.229, with low significance. The α parameter drops to 0.124, and becomes significant at five percent. The Akaike Information Criterion selects the smaller model over the larger model, and the mean squared errors from the two models are almost identical indicating no in-sample predictive benefit from including the ε term.

Column three reports parameter estimates for our model applied to the spreadsheet data. The coefficient of external influence a is 0.00155, similar to that for word processors and compared to 0.00069 in Givon *et al.* (1995). The legal owners' influence parameter b_1 is negligible, and far below the external influence parameter b_2 of 0.0509. In Givon *et al.* (1995), the estimated parameters are larger and comparable at 0.0976 for the b_1 parameter and 0.104 for b_2. Our α parameter is 0.224 compared with 0.121 in Givon *et al.* (1995). The error variance is 3,790,000 implies a standard deviation for monthly legal and pirate acquisitions of 1,900 units per month. The estimate for the ε parameter is 0.0684, so that the marginal propensity to pirate rises with the number of pirates. Except for the variance parameter, significance is low.

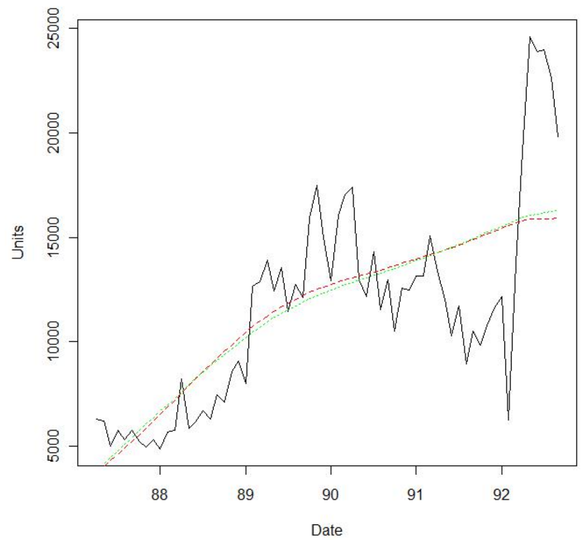
Column four shows the model when ε is excluded. The a, b_1, and σ^2 parameters are similar to the model with it. The b_2 parameter rises to 0.114, and the α parameter drops to 0.101. Both are now significant at five percent. The Akaike Information Criterion selects our model with variable marginal propensity to pirate, and the model offers a non-trivial reduction in mean squared error.

The performance of our model vis-*à*-vis the restricted model is mixed. The ε parameter estimates are plausibly positive and low in value. With the word processor data, the extra variable offers no improvement in fit and weakens the significance on the α parameter, but not the other parameters. With the spreadsheet data, there are noticeable gains for the fit, but the parameter significance worsens perhaps indicating that qualitative behaviour of the larger model better describes the data but the functional form is not correctly specified. We examine these issues in the next subsections.

A further notable point is the insignificance of the legal internal influence in any specification. The estimates point to the only possibly statistically significant internal influence coming from past acquirers of pirate copies.

Figure 1.1 shows the predicted sales as generated by the Kalman filter at our estimated parameters. The top panel shows the fitted sales for word processors in our model (column one in table 1.1, with red dashes) and in the restricted model (column two, with green dots). Our model fits the data better across most of the period except towards its end where its predictions are lower than the restricted model, and far lower than the suddenly hiked sales. The extra parameter available in our model allows for better fitting but comes at a cost in that pirate sales dominate late in the period, if the optimal ε parameter is positive. The legal sales are lower as a result. In the bottom panel, we see the fitted sales for spreadsheets for our model (column three), and for the restricted model (column four). The fit is comparable between the two models for most of the period, but at the end of the period our model fits much better the sudden fall in sales. The reason for the relative fit is that the extra flexibility in our model allows for comparable fit quality over most of the curve, and then better fit to the late fall as pirate sales displace legal sales. The different directions of the sales shifts at the end of the period explains why the mean squared error for our model with the word processor data is the same as the restricted model, whereas it is

Figure 1.1: Predicted and actual sales for word processors (top) and spreadsheets (bottom). Red dashes are for the model with estimated ε, green dots are for the model with ε set at zero



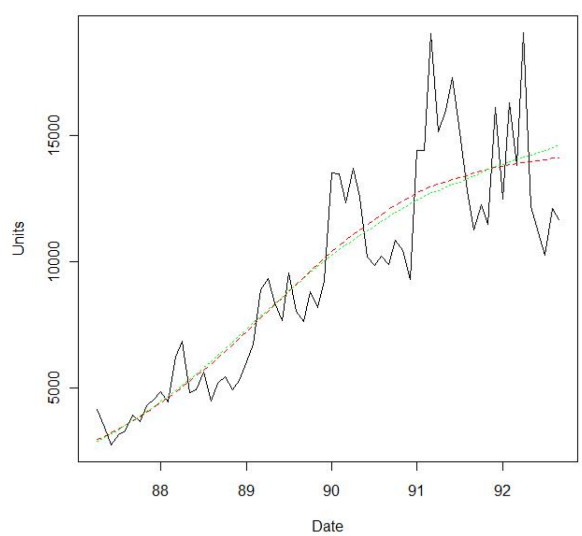
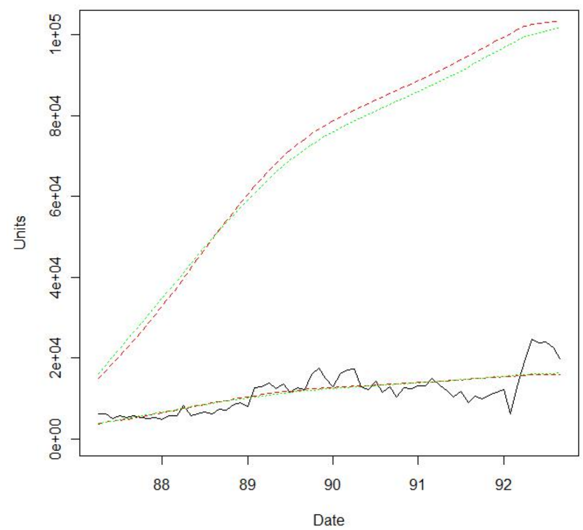
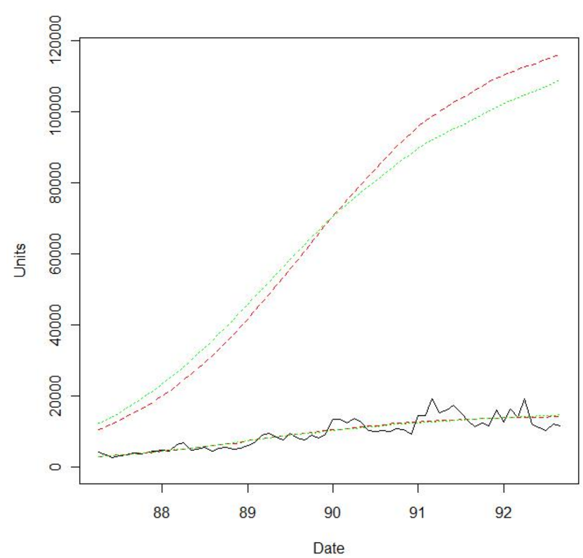


Figure 1.2: Pirate acquisitions, predicted sales, and actual sales for word processors (top) and spreadsheets (bottom). Red dashes are for the model with estimated ε, green dots are for the model with ε set at zero





much lower with the spreadsheet data.

Figure 1.2 shows the same graphs with pirate acquisitions included. The top panel shows forecast piracy for the word processor data. Our model, following the upper line with red dashes, shows pirate acquisitions rising quickly to account for most software acquisition. A similar path is shown for the restricted model, which is the upper line marked by green dots. Piracy incidence in our model is slightly lower than that in the restricted model at the start of the period but exceeds it later by another small amount, with the point of equality occurring quite early on at the end of 1988. Our model includes the extra term accelerating new pirate acquisitions at high rates of past pirate adoptions, so that early piracy tends to be lower and late piracy higher than in the absence of the extra coefficient.

The lower panel shows the corresponding curves for the spreadsheet data. Our model and the restricted model again show similar shapes. The restricted model has a shallower increase, so that our model again forecasts lower incidence of piracy when its prevalence is low, but greater incidence when its prevalence is high. Our model's forecasts exceed those of the restricted model from early 1990, and the gap is moderately large at high piracy prevalence. The larger gap for spreadsheets than word processors is due to the higher estimated ε coefficient for the spreadsheet data.

1.4.2 Out of sample performance

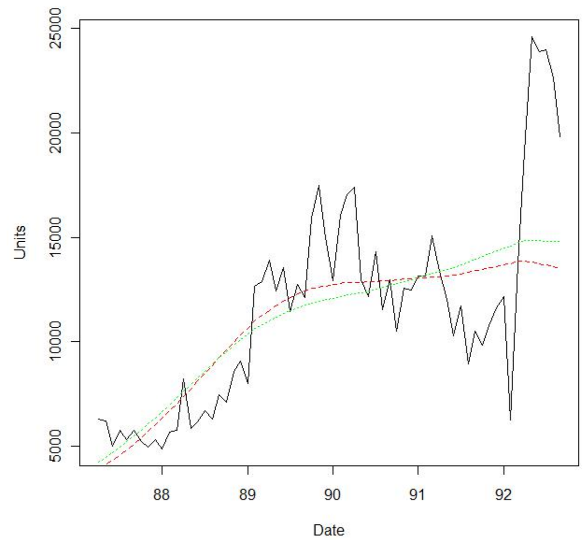
This section compares the predictive performance of our model with that of the restricted model. To do so, we re-estimated our model using data from the first 58 periods, retaining the last ten periods for assessing out of sample fit. For the word processor data, the out of sample period is marked by a large sales jump, while for the spreadsheet data the period saw a possible sales growth slowdown.

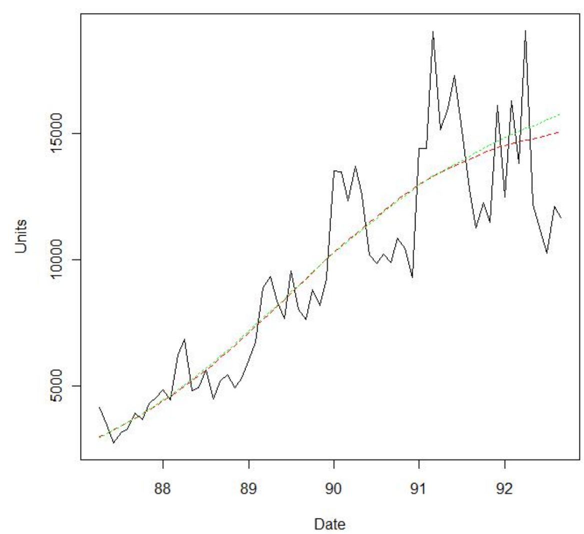
Table 1.2: Parameter estimates in-sample and MSEs out of sample

	WP	WP	S	S
a	0.00183	0.00242	0.00164	0.00161
	0.00187	0.00179	0.00336	0.00207
b_1	0.00252	0.00000	0.00075	0.00001
	0.239	0.194	0.587	0.305
b_2	0.0594	0.145 ***	0.0556	0.106 *
	0.128	0.044	0.406	0.055
α	0.291	0.105 ***	0.199	0.105 **
	0.449	0.0219	1.17	0.0411
σ^2	0.00413 ***	0.0053 ***	0.00309 ***	0.00314 ***
	0.000263	0.000419	0.000473	0.000477
ε	0.0843		0.056	
	0.136		0.462	
MSE, o.o.s. (%)	119	100	83	100

Standard deviations are shown below the coefficients. *** denotes a p-value of less than 0.01, ** of less than 0.05, * of less than 0.1. MSEs out of sample are expressed as percentages of the MSE out of sample for the corresponding restricted model. σ^2 is reported in units of 10^9. WP means word processor and S means spreadsheet.

Figure 1.3: Predicted and actual sales for word processors (top) and spreadsheets (bottom), with ten out-of-sample periods. Red dashes are for the model with estimated ε, green dots are for the model with ε set at zero





The results are in table 1.2. Column one shows the estimates for our model applied to the word processor data. The a parameter of external influence is 0.00183, a little higher than the estimate over the whole range. The b_1 internal legal influence parameter is economically and statistically inconsequential. The b_2 internal pirate influence parameter is 0.0594, slightly below the whole domain estimate. The legal share parameter α is 0.291, far above the whole period value. The variance estimate σ^2 is 0.00413, under half of the full period estimate that includes the sudden sales growth. The estimate of the marginal propensity to pirate parameter ε is 0.0843 compared with the full sample ε estimate of 0.0226. The parameter significance is generally low except on σ^2, and very low on b_1.

Column two shows similar parameters for the restricted model estimated on the word processor data, without ε. The pirate internal influence parameter is fifty percent higher than its full period estimate. The legal share parameter is a little lower. Both these parameters become significant at one percent, unlike the full period estimate or the estimate for the model with variable propensity to pirate.

Our model has a much higher out of sample MSE than the restricted model. Including the variable marginal propensity to pirate worsens fit in this case. The positive ε coefficient results in the share of pirate acquisitions rising over time and the share of legal acquisitions falling, which leads to a far better fit than the restricted model over the in sample period (figure 1.3, top panel). However, the curvature in our predicted sales curve means they lie below the predicted sales of the restricted model after the unprecedented sales jump in the out of sample period.

Column three has the parameter estimates for our model using the spreadsheet data. The external influence, internal legal influence, and legal share parameter are all close to their full period estimates. The internal pirate influence parameter is even smaller than for the full sample, and the error variance parameter is moderately lower. The marginal propensity to pirate parameter is also similar to the value for the whole period, and is positive. Except the variance parameter, significance is low.

The spreadsheet parameter estimates with the ε parameter set to zero are in column four. The estimated volatility is twenty percent lower, but otherwise the parameters are similar to their full period estimates in size and significance.

The mean squared error in spreadsheet sales projection for our model is only 83 percent of the MSE for the restricted model. In our model, the positive ε parameter means that the share of new piracy rises as the number of past pirates increases, so that legal sales' share declines. Legal sales are lower in our model than in the restricted model during the sample period, tracking the decline in actual sales (figure 1.3, bottom panel). The ε parameter is quite high at 0.056, so that the gap is quite large which accounts for the size of the MSE forecast gain.

The non-additive functional form meant that we could not verify the error correlation assumptions necessary to run Clark-West tests (Clark and West, 2007) of the extra variable offering no predictive gains. When the tests were run under uncertain assumption validity, the null of no gains was rejected at ten percent for spreadsheets (assuming no autocorrelation in the data). Significance fell a little on allowing for first order autocorrelation.

Our model seems to capture behaviour over periods without large sales jumps better than the restricted model. However, the restricted model offers more robust predictions when faced with shocks biased against the general direction of movement. It is unclear, based on the available data, whether such shocks are inherent to the system and occur frequently. If they are and do, then more extensive misspecifications may be preferable to less misspecified models if the partial misspecification decreases predictive accuracy after the shock.

1.4.3 Alternative error specifications

Our model in equations 1.2 describes the errors in the legal sales and pirate acquisition series by a bivariate normal distribution. In order to achieve parameter identification, our base estimations restricted the variance-covariance matrix $\boldsymbol{Q}$ to be a multiple of the identity matrix. In this section, we compare our estimates under other error specifications.

We consider four $\boldsymbol{Q}$ specifications, applied to the word processor and spreadsheet series in turn. The first specification puts the variance for the larger pirate series to be twice the variance for the legal series, so $q_{1,1} = \sigma^2$ for some constant σ^2, $q_{2,2} = 2\sigma^2$, and $q_{1,2} = q_{1,2} = 0$. The second specification allows for positive correlation between the legal sales and pirate acquisitions, setting $q_{1,1} = q_{2,2} = \sigma^2$ and $q_{1,2} = q_{1,2} = \sigma^2/2$. Thirdly, we specify negative correlation between the two series, so $q_{1,1} = q_{2,2} = \sigma^2$ and $q_{1,2} = q_{1,2} = -\sigma^2/2$. In the fourth specification, heteroscedastic errors are allowed so $q_{1,1} = q_{2,2} = N_t\sigma^2$ and $q_{1,2} = q_{1,2} = 0$, recalling that N_t is market capacity at time t, which we express in millions.

Our model was re-estimated with each of these variance specifications. The coefficient estimates are given in Table 1.3. The word processor results are presented in the first four columns. With doubled pirate variance in column one, the coefficients are similar to the base estimates in value and significance. The marginal propensity to pirate rises a little more quickly. The

Table 1.3: Parameter estimates with alternative error specifications

	WP	WP	WP	WP	S	S	S	S
	Err. × 2	Pos. cor.	Neg. cor.	Het. err.	Err. × 2	Pos. cor.	Neg. cor.	Het. err.
a	0.00139	0.00163	0.00123	0.00217	0.00163	0.00161	0.00157	0.00169
	0.0046	0.00579	0.00701	0.00163	0.00493	0.00443	0.00407	0.00183
b_1	0.0911	0.334	0.381	0.00007	0.000104	0.000989	0.000366	0.00232
	0.786	1.59	1.49	0.293	1.36	0.719	0.495	0.367
b_2	0.0864	0.101	0.000769	0.0518	0.103	0.0597	0.044	0.0524
	0.386	0.378	0.0999	0.176	0.831	0.458	0.318	0.28
α	0.175	0.103	0.226	0.317	0.109	0.188	0.259	0.207
	0.483	0.178	0.472	0.74	0.724	1.18	1.52	0.896
σ^2	0.0108 ***	0.0108 ***	0.0103 ***	0.00242 ***	0.004 ***	0.00385 ***	0.00375 ***	0.000936 ***
	0.00198	0.00209	0.00206	0.000491	0.000813	0.000754	0.000716	0.000213
ε	0.0283	-0.0147	0.0454	0.0924	0.00776	0.0535	0.0826	0.0624
	0.202	0.116	0.216	0.224	0.454	0.477	0.494	0.354
AIC	1287.0	1287.5	1286.4	1261.1	1220.4	1217.9	1216.1	1197.3
MSE (%)	100	100	98	104	105	101	99	101

Standard deviations are shown below the coefficients. *** denotes a p-value of less than 0.01, ** of less than 0.05, * of less than 0.1. MSEs are expressed as percentages of the MSE for the base estimations (columns one and three of table 1.1). σ^2 is reported in units of 10^9. WP means word processor and S means spreadsheet.

AIC and MSE are no different. For positive correlation in column two, the estimated effect of legal internal influence is much larger ($b_1 = 0.334$) than in the base model. The marginal propensity to pirate declines as the number of pirate copies rises ($\varepsilon = -0.0147$), unlike in the base estimates. The positively correlation provides a route by which pirate acquisitions influence legal sales, and which can therefore account for the diminished importance of the direct influence of piracy on diffusion in this estimation. The AIC is higher for this specification and the mean squared errors are the same.

Column three shows the estimates with negative correlation. Parameter estimates for external influence and variance within series are similar to the base estimate. However, the estimates of the legal internal influence and the legal share parameter are much larger, at 0.381 and 0.226 respectively. Thus, for small times t the proportion of past legal adopters who induce new legal adoptions is $0.381 \times 0.226/N_t = 0.086/N_t$. The estimated effect of pirate internal influence is negligible. Taking also into account the number of new adoptions induced by past legal adoptions and the size of the external influence parameter, the early legal diffusion looks like a standard univariate Bass diffusion. The marginal propensity to pirate rises much more quickly in this specification than in the base model (ε equals 0.0454 compared with 0.0226). The AIC and MSE are lower. In this specification, piracy acts primarily to displace legal diffusion without promoting it.

Column four shows the parameters for the model with heterogeneous errors. Compared with the base model parameters, the external diffusion parameter is moderately larger. The legal internal influence coefficient is negligible, and the pirate internal influence coefficient is much the same. The marginal propensity to pirate rises much more quickly in this specification ($\varepsilon = 0.0924$). The AIC is lower, but the MSE increases by a larger percentage.

Parameter estimates for the spreadsheet data are shown in columns five to eight. The parameters for the double pirate error specification are shown in column five. The external influence and legal internal influence parameters are much the same. The variance coefficient is similar at 0.004. The pirate internal influence parameter is almost doubled at 0.103, while the legal share parameter is halved at 0.109. The rise in marginal propensity to pirate is positive and low, with ε at 0.00776 compared with 0.0684 in the base specification. Significance is generally low, the AIC is higher and the MSE increases by five percent.

In column six, the results are shown for the positive correlation error specification. The parameter estimates are not too dissimilar from the base specification. The AIC and MSE are higher. The parameters for the negative correlation error specification are shown in column seven. The parameters are similar to the base specification, with the marginal propensity to pirate parameter a bit larger. The AIC and MSE are both a little lower. The parameters for the heterogeneous error specification are in column eight. They are again similar to the base specification. The AIC improves by two percent and the MSE worsens by one percent.

In summary, the alternative error specifications broadly support an increasing marginal propensity to pirate. For both the word processor and spreadsheet data, the negative correlation specifications reduce the AIC and the MSE. For the word processor data, the resulting model shows piracy growing rapidly and making little contribution to legal diffusion. Parameter significance is generally low.

1.4.4 An alternative model

1.4.4.1 The alternative specification

We noted earlier that our model gives plausible values for the ε parameter and some improvements in fit, but with low parameter significance. In this section, an alternative specification is examined that exhibits the same broad type of qualitative behaviour. The aim is to see if better fitting parameters can be produced, or at least verification of the qualitative outcomes.

The alternative specification makes the legal share α decline as the number of cumulative pirate adopters rises. The share of new internally influenced adopters who buy is revised to $\alpha/(1+\max(Y_t,1)^{\varepsilon})$, where Y_t is the number of pirates. The remaining share, $1-\alpha/(1+\max(Y_t,1)^{\varepsilon})$, acquires a pirate copy. We omit the piracy multiplier $\max(Y_t,1)^{\varepsilon}$ described in the model in section 1.2. In the new model, piracy has no accelerating effect unlike the earlier model, and instead only displaces legal sales.

Algebraically, the model is

$$
\begin{aligned}
dX_t &= (\left[a+\tfrac{\alpha}{1+\max(Y_t,1)^{\varepsilon}}\tfrac{b_1X_t+b_2Y_t}{N_t}\right](N_t-X_t-Y_t))dt+dw_1\\
dY_t &= (\left[(1-\tfrac{\alpha}{1+\max(Y_t,1)^{\varepsilon}})\tfrac{b_1X_t+b_2Y_t}{N_t}\right](N_t-X_t-Y_t))dt+dw_2
\end{aligned}
\tag{1.31}
$$

where $\boldsymbol{dw}=(dw_1,dw_2)\sim N(0,dt^2\boldsymbol{Q})$, and $\boldsymbol{Q}=\sigma^2\boldsymbol{I}(2)$.

We repeat the state space representation in section 1.3.2. Now the vector $\boldsymbol{f}$ is given by

$$f_1 = \left[a + \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}} \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \tag{1.32}$$

$$f_2 = \left[(1 - \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}}) \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \tag{1.33}$$

and the components of the matrix $\boldsymbol{F}$ are given by the following expressions:

$$\begin{aligned} \boldsymbol{F}_{1,1} = & \left[\frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}} \frac{b_1}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \\ & - \left[a + \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}} \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] \end{aligned} \tag{1.34}$$

$$\begin{aligned} \boldsymbol{F}_{1,2} = & \left[-\varepsilon \max(Y_{t-1},1)^{\varepsilon-1} \frac{\alpha}{(1+\max(Y_{t-1},1)^{\varepsilon})^2} \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right. \\ & \left. + \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}} \frac{b_2}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \\ & - \left[a + \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}} \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] \end{aligned} \tag{1.35}$$

$$\begin{aligned} \boldsymbol{F}_{2,1} = & \left[(1 - \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}}) \frac{b_1}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \\ & - \left[(1 - \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}}) \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] \end{aligned} \tag{1.36}$$

$$\begin{aligned} \boldsymbol{F}_{2,2} = & \left[\varepsilon \max(Y_{t-1},1)^{\varepsilon-1} \frac{\alpha}{(1+\max(Y_{t-1},1)^{\varepsilon})^2} \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right. \\ & \left. + (1 - \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}}) \frac{b_2}{N_t} \right] (N_t - X_{t-1} - Y_{t-1}) \\ & - \left[(1 - \frac{\alpha}{1+\max(Y_{t-1},1)^{\varepsilon}}) \frac{b_1 X_{t-1} + b_2 Y_{t-1}}{N_t} \right] \end{aligned} \tag{1.37}$$

1.4.4.2 Results for the alternative specification

Table 1.4: Parameter estimates for the alternative model form

	WP	WP	S	S
a	0.0016	0.00167	0.00115	0.00135
	0.0039	0.00391	0.00525	0.00271
b_1	0.167	0.283	0.000853	0.00000
	1.27	1.25	0.932	0.551
b_2	0.11	0.0857	0.112	0.113
	0.237	0.229	0.18	0.0854
α	0.246	0.245 ***	0.33	0.208 **
	0.628	0.0947	2.43	0.0903
σ^2	0.0108 ***	0.0107 ***	0.00403 ***	0.00407 ***
	0.00209	0.00203	0.000827	0.000752
ε	0.000467		0.0503	
	0.326		0.664	
AIC	1287.0	1285.0	1220.8	1219.4
MSE (%)	100	100	99	100

Standard deviations are shown below the coefficients. *** denotes a p-value of less than 0.01, ** of less than 0.05, * of less than 0.1. MSEs are expressed as percentages of the MSE for the corresponding restricted model. σ^2 is reported in units of 10^9. WP means word processor and S means spreadsheet.

Table 1.4 shows the results of estimation for the alternative model. In column one, we see the model fitted to the word processor data. The external influence parameter is 0.0016, comparable with our estimate for our main model. The legal internal influence parameter is 0.167, higher than the main model estimate but comparable with Givon *et al.* (1995). The same is true for the pirate internal influence parameter. The α parameter is larger than for the main model, but the two are not directly comparable. In our model and for low values of the ε parameter, the α parameter is twice the legal share. Error variance estimates are unchanged. The ε parameter is positive, indicating the pirate share of internally influenced adoption rises as the number of pirate copies rises. Parameter significance is low except for variance. Column two fixes the pirate share, and produces almost the same estimates as column two of table 1.1 whose specification is identical. Differences arise from slight variations in numerical convergence. Including the variable marginal propensity to pirate raises the AIC and does not change the MSE.

Column three reports the fitted parameters for the spreadsheet data. The external influence parameter is comparable with that in the main model, as is the negligible legal internal influence coefficient and the error variance estimate. The pirate internal influence parameter is 0.112, which is twice as high as for the main model and comparable with Givon *et al.* (1995). The legal share is 0.165 after adjustment for comparison with the earlier work, making it lower than in the main model but a little higher than in Givon *et al.* (1995). The ε parameter is moderately positive, indicating rising marginal propensity to pirate. Its significance, as for the other parameters except error variance, is low. As shown in column four, the model with ε set to zero has much the same parameters as the constrained main model. Its AIC is slightly lower, but has higher MSE than the unconstrained model in column three.

In summary, the alternative model also identifies a rising marginal propensity to pirate in the word processor and spreadsheet data. The model performance is not quite as good as for the main model. Perhaps the acceleration of pirate sales due to piracy, which is present in the main model but missing from this specification, captures an aspect of the data generating process.

1.5 Conclusion

This paper has examined diffusion of computer software in the presence of piracy. It has generally found that the marginal propensity to pirate rises with the number of past pirate copies. It has found that piracy is responsible for most of the internally influenced diffusion in the spreadsheet market in the period under examination. In the word processor market, an error specification with negative correlation outperformed other specifications and indicated that only legal sales were responsible for internally influenced diffusion.

A number of avenues for future work are suggested. One of them follows from noting that a rising propensity to pirate alters the timing of welfare and profit emergence. Further work could examine their dynamics and strategic behaviour undertaken by legal sellers in order to manage piracy.

Including the marginal propensity to pirate in the pirate diffusion model offers gains in fit and assumption plausibility. However, they were not entirely functionally convincing, with low parameter significance possibly indicating lack of parsimony. Better specifications of the deterministic components of the model could be sought.

Our model's predictive performance was mixed. It underperformed the restricted model after a large shock contrary to the general sales curvature. Further work could clarify whether these shocks form error corrections to drifts away from the restricted model, or are not systemically related to the models here. In the latter case, analysing the frequency of shocks and their direction would help to clarify the probability and severity of predictive underperformance.

More general specification of stochastic components has allowed us to strengthen Givon *et al.* (1995)'s and Haruvy *et al.* (2004)'s findings on spreadsheets and contradict them on word processors. For the latter point, it is conceivable that the difference between the results is that our allowance of negative error correlation strips out a source of interaction which is forced to be included in the deterministic components of their model. Further work could further distinguish between deterministic and stochastic interactions. It could also allow for serial correlation, for example in a revised state space formulation.

Our work finds contrasting effects of past piracy on the word processor and spreadsheet market. Qualitative studies could examine the reasons for the difference. Conceivably it arises because of the presence of a dominant but declining word processor product (Word Perfect) over the period without an equivalent in the spreadsheet market, or due to different corporate strategies by market leaders.

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Chapter 2

Welfare implications of piracy with dynamic pricing and heterogeneous consumers

2.1 Introduction

Piracy can involve extraction of profits by pirate providers from legal producers, as pirate copies may be offered at prices as or more attractive than those of legal goods. Companies may attempt to avoid piracy's effects by various means, including using price reductions to capture a larger share of the market. Such a strategy involves lowering prices below those which would be optimal in the absence of piracy. Legal sellers can avoid some of the wealth loss associated with piracy, but their price reductions can transfer surplus to consumers.

Skimming on the other hand is a means by which companies can increase profits through successive price reductions. It involves selling at prices equal to the marginal valuations of consumers, first by setting prices to sell only to the highest valuing consumers, then reducing prices to sell only to the next highest valuing consumers, and so on. Companies can thereby extract all surplus from consumers. The surplus transfers due to skimming and piracy prevention can thus go in different directions.

In this paper we examine the welfare trade-offs between the two pricing strategies. We address three main questions. Firstly, does piracy raise or lower aggregate welfare when these countervailing strategies operate? Secondly, how does welfare divide between legal sellers, pirate providers, and consumers? Thirdly, how does market growth affect these welfare outcomes?

We find that in markets with a fixed size, total welfare rises with the piracy rate. The best way for the legal seller to avoid piracy's rising impact is to reduce prices early, reducing the discounting on the value of the goods and limiting the extent of skimming. Consumers have a strong preference for high rates of piracy, while pirate providers like moderate rates that do not trigger price responses from legal sellers. Legal sellers are adverse to all piracy.

In growing markets, total welfare falls as the piracy rate rises. With higher rates, the legal seller best avoids piracy's effect by delaying product launch until the market is large. Although skimming becomes less important, the pricing strategy to avoid piracy results in greater delays in sales and incomplete satisfaction of market demand. Consumers benefit from high rates of piracy, but to a lesser extent than in fixed size markets. Pirate providers prefer moderate to moderately high rates, and legal sellers like low rates.

Section 2.2 describes related literature. Section 2.3 presents our model and section 2.4 describes the numerical analysis method. Section 2.5 looks at pricing, sales time, and welfare in the presence of piracy when market size is fixed, while section 2.6 does the same when the market is growing. Section 2.7 concludes.

2.2 Related literature

In this section we briefly look at theoretical literature relating to the main themes in our model. Prior work suggests that piracy may increase or decrease aggregate welfare. An early stream of analysis examines static mechanisms, involving the breaking of a legal seller's monopoly control by pirate providers and the relative productive efficiencies of legal and pirate sellers. Later writers extend the models in various ways, including examination of the welfare effect of government or company interventions against piracy, and outcomes in dynamic settings. Other writers examine legal sellers' profits in the presence of piracy, suggesting various mechanisms by which piracy can increase profits. A small number of papers present dynamic models examining the contrasting effects on profits of piracy and intertemporal price discrimination.

The short run effect of piracy is analysed in Besen (1986). Production of a good can occur by legal means or pirate means, with their relative efficiencies determining which productive form gives welfare maximising outcomes. When legal sellers are capable of capturing some of the value of pirate resale, effectively making piracy an alternative production technology, piracy may also be profit maximising if it is the more efficient productive technology. Johnson (1985) notes the ambiguity in short run welfare effects due to piracy. Greater inefficiency of pirate production is offset by surplus generated when more agents acquire the good in response to the cost of pirate acquisition being lower than legal prices.

Ahn and Shin (2010) look at the welfare consequences of piracy prevention strategies. They find government enforcement of copyright law can be more welfare enhancing than technological protection measures for digital goods. Tsai and Chiou (2012) examine the effects of anti-counterfeiting enforcement on welfare, and find ambiguous outcomes. They decompose welfare into consumer surplus and legal profit, with counterfeiter profit assumed to be zero under a market entry condition.

A small number of researchers have looked at how piracy affects welfare in a dynamic framework. In a simulated model, Khouja *et al.* (2008) observe that the total number of sales for any level of piracy is close to the total market size, so pirate sales compensate for restrictions on acquisitions due to legal prices. The authors do not calculate discounted welfare although their model allows it, which would be informative about the welfare effects of piracy. In Herings *et al.* (2009), the cost of pirate copying declines directly with the number of copiers. Discouraging piracy by increasing its cost reduces welfare. The authors do not present the dynamic patterns of emergence.

The effect of piracy on legal sellers' profits has been studied in the literature, with various mechanisms proposed by which piracy can be profit enhancing. Minniti and Vergari (2010) suggest that if piracy of one good increases the utility derived from purchase of another good, then profits can be increased by it. Banerjee (2013) notes that profits may rise as piracy goes up if network externalities are simultaneously present and sufficiently strong. A number of papers (Givon *et al.*, 1995, 1997; Prasad and Mahajan, 2003; Haruvy *et al.*, 2004; Liu *et al.*, 2011) use dynamic analyses to suggest that piracy can benefit legal sellers. A common theme is that piracy can act as a control on diffusion, either to reach a certain diffusion rate or network size. The analyses also generally include assumptions to stop piracy getting out of hand, and have absent or transient consumer heterogeneity.

By contrast, Khouja and Smith (2007) present a dynamic model of piracy where consumers exhibit persistent heterogeneity and intertemporal price discrimination can occur. They show that piracy leads to departure from skimming and reductions in profit. In Khouja *et al.* (2008)'s dynamic analysis, the market for a product consists of a number of individuals each of whom may make a pirate copy from a fixed number of neighbours if the latter have the product. Skimming by the legal seller is profit maximising for low numbers of neighbours (when piracy is less extensive), but is not optimal as the numbers of neighbours rises.

In modelling skimming and departures from it in the presence of piracy, Khouja *et al.* (2008) and Khouja and Smith (2007) overlap with our model and results. However, whereas Khouja *et al.* (2008) use simulation and Khouja and Smith (2007) use algebraic solution for pricing, we use a flexible numeric solution to solve our dynamic programming model. Their primary concern is not welfare, and Khouja *et al.* (2008) consider a fixed size market and Khouja and Smith (2007) examine a contracting one, compared with the expanding market we examine and that leads to our dynamic welfare trade-off.

2.3 Model

In this section, we describe our model of information good pricing in the presence of piracy. Diffusion is divided into acquisitions from a legal seller and pirate providers. The split is decided by competition between the two groups. Potential buyers are heterogeneous in their valuation of the good, so that price acts as a control variable on diffusion. The number of pirate providers rises with the number of previous buyers. Aside from pirate entry, additional dynamics in the model are induced by market growth. The legal seller performs dynamic optimisation over pricing, taking into account the dynamics within the model.

There is a single legal producer of an information good. The legal producer is profit maximising and possesses the ability to produce the information good developed from their own research and development. The legal producer can instantly produce copies of the good at a constant unit cost. As the cost of production can be absorbed into net price, we without loss of generality set the cost to zero.

At time t, there are k_t pirate providers of the good. Pirate providers produce copies of the good innovated by a legal seller. They initially get the production technology by acquiring a copy of the good from a legal seller or pirate provider. The technology may be as little as computer software and a DVD burner. Pirate providers are a subset of current good users, so as the number of past acquisitions rises, the number of pirate providers may increase too. We assume that the number of pirate providers is related to the number of goods previously sold by the equation $k_t = s(\sum_{\tau=1}^{t-1} S_\tau)^h$ for $t > 1$, $s > 0$, and $h > 0$ (and $k_0 = 0$) where S_τ is all goods sold at time τ. Fractional numbers of pirate providers are allowed, representing providers who are less active than average. h is the elasticity of the number of pirate providers with respect to past sales. Its precise value does not change the main pricing mechanisms of interest here, so we take it to be one and term the coefficient of proportionality s as the piracy rate (see Khouja and Smith (2007), who present a model where the number of copies pirated in a period is a fixed proportion of past sales). The modifying effects of different values of h are described in the conclusion. The unit cost of pirate production is constant and we absorb it into the net price charged by pirate providers, so again we can without loss of generality set production cost at zero.

The population who could have acquired the good by time t is denoted $N(t)$. $N(t)$ includes people who have already acquired the good and those who have not. We term this population as market size, as they are people who will acquire the good if they are offered it at a price below their valuation, but may not yet have been offered at such a price and prior to the product launch may not even be aware of it. $N(t)$ can vary over time, for example with a rise in the number of owners of a technology necessary for the information good's usage, such as DVD players or computers. A similar approach to growth in market size is used in Givon *et al.* (1995), and models the number of people who could potentially own the good because they meet the necessary criteria (like DVD player ownership) whether or not they have yet purchased the good (like a DVD). The market size can thus grow independently of the actual market availability of the good. Once the potential adopter has acquired the good, they will not acquire it for a second time.

We denote the number of new potential buyers at time t by $n(t) = N(t) - N(t-1)$. Potential buyers are heterogeneous in their willingness to pay for the good. We discriminate between their willingness to pay for the legally supplied and the pirate supplied good. For the legally supplied good, valuations of the good by consumers entering at time t are distributed uniformly over the interval $[0, V]$ for some constant V (similar to the approach in Khouja and Park (2007), Khouja and Wang (2010), Jeong *et al.* (2012), and Kogan *et al.* (2013)). The number of consumers entering the market at time t with a valuation exceeding a price $p(t)$ is thus

$$\int_{p(t)}^{V} \frac{n(t)}{V} dv = n(t)(1 - \frac{p(t)}{V}) \tag{2.1}$$

As V is a constant, we can choose the units on $p(t)$ to absorb it and leave the aggregate demand function $q_{e,t} = n(t)(1 - p(t))$, where $q_{e,t}$ is the aggregate quantity demanded at time t and $0 \leq p(t) \leq 1$ is the price of the legally supplied good at time t. Similarly, the initial consumers in the first period have an aggregate demand function of $q_{e,1} = N(1)(1 - p(1))$. The aggregate demand at time t arising from both new entrants and previously entered non-users is $q_t(p(t))$.

Pirate suppliers price their good at $p_{pirate}(t)$ at time t. In using the pirate supplied good, buyers choose to bring the quality up to the quality of a legally supplied good and in doing so must pay a proportion c of the legal price $p(t)$. We may optionally consider the extra price to be equal to the cost of quality restoration, so the $cp(t)$ is an additional deadweight loss of pirate production. The effective price of acquiring a pirate copy of the good is thus $p_{pirate}(t) + cp(t)$. Pirate suppliers price to remain competitive with legal suppliers, and set $p_{pirate}(t)$ such that $p_{pirate}(t) + cp(t) = p(t)$, or $p_{pirate}(t) = (1 - c)p(t)$.

Our framework does not explicitly allow for consumers facing piracy risk cost. Although some authors allow for non-zero risk cost (for example Jeong *et al.* (2012)), we consider zero risk cost to be a reasonable assumption in many markets where consumer use of pirated copies is very widespread and the prospect of individual prosecution is low, even if consumer awareness of the issue exists to any degree. For example BSA (2012) estimates 42 percent of all software products installed worldwide in 2011 were pirate copies, and in some developing countries the rates were much higher. Alternatively, we may consider part of the value reduction $cp(t)$ to be due to the expected value loss due to the risk, and part of the restoration cost to arise from taking measures to avoid detection.

Sales at any price are divided so that for each copy sold by the legal seller, each pirate provider sells j copies on average where j may be fractional and less than one. The share of legal sales in total sales is then $1/(1 + jk_t)$, and the share of pirate sales in total sales is $jk_t/(1 + jk_t)$. Since $k_t = s \sum_{\tau=1}^{t-1} S_\tau$, we absorb the constant j into the constant s without affecting our results. Hence aggregate legal sales are

$$\frac{1}{1 + k_t} p(t) q_t(p(t)) \tag{2.2}$$

and aggregate pirate sales are

$$\frac{k_t}{1 + k_t} p(t) q_t(p(t)) \tag{2.3}$$

The legal seller acts to maximise discounted future profits by setting a price sequence $\{p(t)\}$ for $t = 1, \ldots, T$ for some upper time limit T. T measures the period from when the legal seller is first able to sell the good to when demand for the good falls to zero even if some of the initial demand for the good was not satisfied. It is the length of time until a better product emerges and makes the current one obsolete. Because of independent discovery and the general drift in technological improvement (Merton, 1961; Dasgupta and Maskin, 1987), the time T is assumed not to depend on when the product launch occurs. Thus, the legal seller has a finite time in which to exploit their good, and if the seller chooses to price the good so that sales start later than the first period, then the length of sales period is shorter than T. We could assume that the obsolescence date is stochastic, but for clarity about our intended mechanism and for ease of calculation we take the latest possible sales period as fixed at T.

In maximising profits, the legal sellers take into account the exogenous dynamics in market size, and the endogenous dynamics in demand preference and pirate emergence. The legal seller is assumed to have perfect knowledge of all parameters and future dynamics. They face a dynamic programming problem whose objective function to be maximised follows from collecting the above expressions:

$$\sum_{t=1}^{T} \frac{d^t}{1+k_t} p(t) q_t(p(t)) \tag{2.4}$$

where d is the legal seller's discount per period.

2.4 Numerical analysis

We investigate the theoretical properties of the model by solving the legal seller's problem in equation 2.4 through discretisation of the demand function and exhaustive search of pricing sequences with tracking of demand structure. We calculate the properties over a five year period with annual price setting and monthly market growth. These time parameters are set for practical and empirical reasons. The annual pricing is intended to reflect the persistence of prices due to contractual agreements, menu costs, and the increase in option values of delaying purchase (so dampening the effectiveness of a price change). When we have a five year horizon, the number of numerical calculations required by our solution algorithm is relatively limited and the solution is quick. We take five years as the lifetime of our information good, following Liu *et al.* (2011) on software products.

In numerical analysis, we discretise the demand function for new entrants $q_{e,t}$ by dividing the $n(t)$ new market entrants into M equal parts $n(t)/M$, $2n(t)/M$, …, $n(t)$, with corresponding valuation prices $p_1(t), p_2(t), \ldots, p_M(t)$. We find price $p_m(t)$ for any $m = 1, 2, \ldots, M$ by solving for the price at the mid-point of the band, $0.5((m-1)+m)n(t)/M = n(t)(1-p_m(t))$ or $p_m(t) =$

$1-(m-0.5)/M$. Zero demand is obtained at $p_0(t) = 1$. We define $n_m(t)$ to be the number of new entrants with willingness to pay of $p_m(t)$, for $m = 1, 2, \ldots, M-1$. Then $n_m(t) = int(n(t)/M)$ where $int(x)$ denotes the integer part of x. We take the lowest valuation when $m = M$ as additionally including all rounding errors, so $n_M(t) = n(t) - \sum_{m=1}^{M-1} n_m(t)$. The willingness to pay of the initial consumers at time $t = 1$ is similarly discretised. We define $C_m(t)$ as the number of current potential buyers at time t (both from new entrants and previously entered non-users) with willingness to pay of $p_m(t)$.

When the unique offer price in the market is from the legal seller and is $p(t)$, the number of individuals valuing the good at more than $p(t)$ is $\sum_{m \in m_{p(t)}} C_m(t)$ where $m_{p(t)} = \{m : 1-(m-0.5)/M \geq p(t)\}$, which approximates the aggregate demand function $q_t(p(t))$. We can then approximate the equations 2.2, 2.3, and 2.4 for legal sales, pirate sales, and the legal seller's objective function respectively as

$$\frac{1}{1+k_t} p(t) \sum_{m \in m_{p(t)}} C_m(t) \tag{2.5}$$

$$\frac{k_t}{1+k_t} p(t) \sum_{m \in m_{p(t)}} C_m(t) \tag{2.6}$$

and

$$\sum_{t=1}^{T} \frac{d^t}{1+k_t} p(t) \sum_{m \in m_{p(t)}} C_m(t) \tag{2.7}$$

The dynamics of the number of potential buyers in each valuation band are given by $C_m(t+1) = n_m(t)$ if $1-(m-0.5)/M \geq p(t)$ and $C_m(t+1) = C_m(t) + n_m(t)$ otherwise. The dynamic in the number of pirate providers is described by $k_t = s \sum_{\tau=1}^{t-1} \sum_{m \in m_{p(\tau)}} C_m(\tau)$. Starting values are $C_m(0) = 0$ for all m and $k_0 = 0$.

The expression 2.7 for maximisation may be considered a weighted sum of the per period sales, where the weights are themselves endogenously defined as the legal seller's current shares. The per period sales are constrained by the market growth. This interpretation helps to clarify the subsequent role of piracy, which reduces the weights over time and whose effect depends on the possible set of sales.

For a given parameter set, the legal seller's problem is solved to give a sequence of prices as the control variable and a sequence of sales as the response variable. We solve the problem by a dynamic programming algorithm over the five year period. The algorithm tracks the price sequences that lead to the highest discounted revenue. At each time period, the possible non-user distributions at the start of the period are found by taking the possible distributions at the end of the previous period and increasing market size if growth occurs in the period. The market growth is spread evenly over all valuation points, and increases at the specified speed. For each distribution at the start of the period, new distributions are generated by having the legal seller offer to sell at each possible price. The possible prices at the start of each year are the valuation prices plus a higher price corresponding to no sales, and for all other months are constrained to be the previous month's price. At each price and each starting distribution, non-users at valuation levels exceeding the price buy the good and leave the non-user distribution. Each resulting distribution has an associated price sequence comprising the price sequence associated with the preceding distribution together with the present price, and a sales sequence generated similarly. We iterate over all periods to obtain final price and sales sequences after five years. The sequence of numbers of pirate sellers is calculated as the specified proportion s of the one period lagged cumulative sales sequence. We retain the pair with the highest discounted revenue, giving the optimal price choices of the legal seller. Discounted revenue to the legal seller is calculated as the legal share of total revenue divided between legal and pirate sellers.

Table 2.1: Parameter values

Parameter	Value
Piracy rate (s)	0 - 0.0001
Elasticity of pirate numbers with respect to past sales (h)	1
Initial number of pirate providers (k_0)	0
Initial market size ($N(0)$)	100000; 0
New buyers at time t ($n(t)$)	0; 1000
Number of time periods (T)	60
Discount per period (d)	0.99
Periods in which prices are set	1, 13, 25, 37, 49
Number of demand function divisions (M)	5
Potential buyers at time 0 with valuation $p_m(0)$ ($C_m(0)$)	0

In all solutions we hold the monthly discount factor d constant at a rate of $1/1.01$, equivalent to annual discounting of 12.7 percent. The market growth is specified to be zero or a positive constant. We use five valuation points on the discretised demand distribution ($M = 5$). Table 2.1 summarises the parameter values used. The effects of varying parameter values and assumptions are discussed in sections 2.5, 2.6, and 2.7.

The estimation was implemented in the R programming language (R Development Core Team, 2009). The code is available from the author's website [1].

2.5 Welfare with fixed market size

2.5.1 Pricing

Figure 2.1: Price variation as a function of the piracy rate with fixed size. The rates are 0 (circles), 0.000005 (triangles), and 0.0001 (crosses).

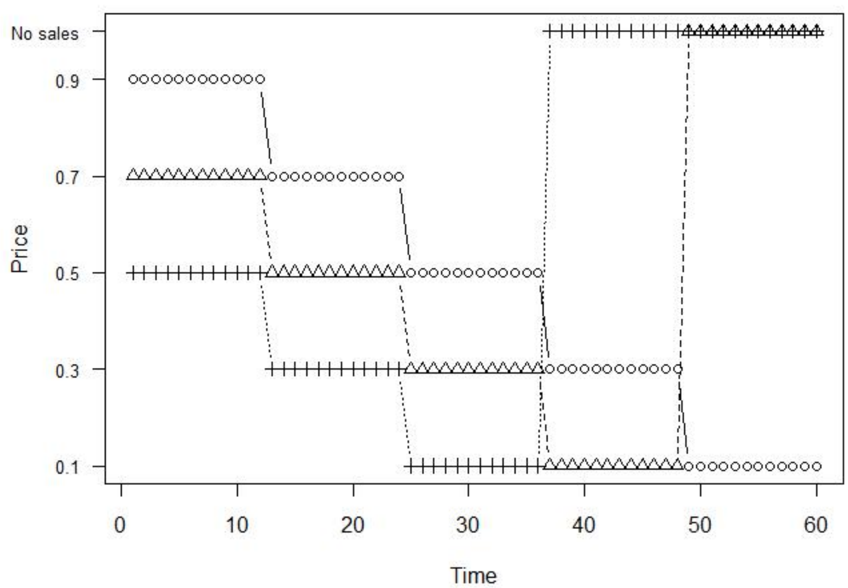


Figure 2.1 shows how dynamic prices change as the piracy rate rises, when market size is held constant (at 100,000). The circles indicate prices when there is no piracy. Prices decline four times between every period, as

[1] http://ebasic.easily.co.uk/02E044/05304E/pricing_info_goods_EJOR.html

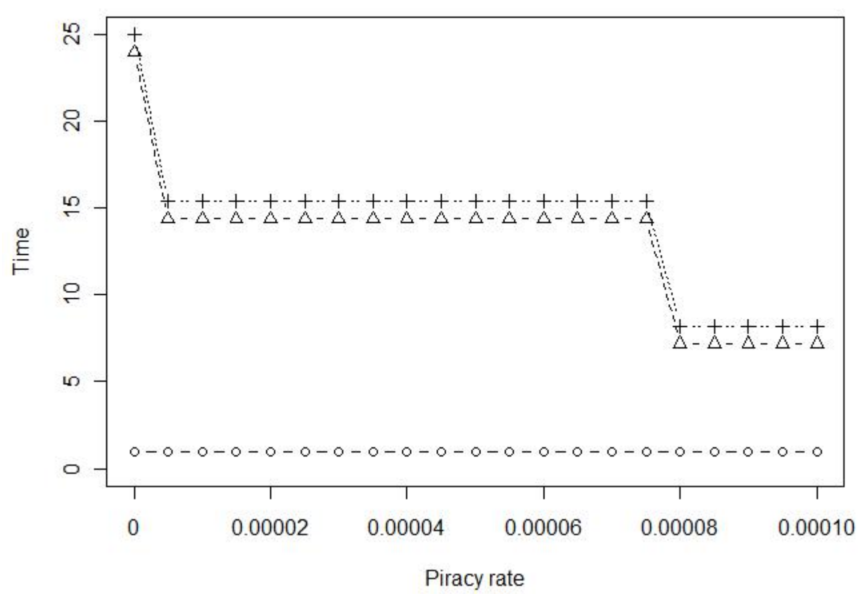
the legal seller sells to each valuation band in turn. Demand is fully met in the final period as prices reach the lowest valuation band. Triangles indicate pricing at a higher rate of piracy, where piracy's effect is equivalent to sharing sales with $100000 \times 0.000005 = 0.5$ other identical legal sellers at the end of the product life. There are three price declines that occur at the end of the first three years, falling from the second highest valuation band to the lowest in year four. The legal seller then exits the exhausted market. Crosses show pricing when piracy reaches the equivalent of ten legal sellers. Prices fall from the middle to the lowest valuation band after three years, followed by market exit from the fourth period onwards. Considering all the pricing behaviour together, we see that pricing starts at a high valuation band, it finishes in the lowest band with all demand satisfied, and price changes become more compressed near the start of the period as piracy increases.

We can rationalise the observations by reference to the legal seller's profit maximisation. In the absence of piracy, the company can extract all surplus from the market by charging each buyer their highest willingness to pay. The company can do so by practicing intertemporal price discrimination. If discounting is not excessive relative to the gains of intertemporal price discrimination - that is, relative to the gap between valuation bands - then skimming will be practiced.

As the piracy rate increases, pirate providers will emerge as competitors in proportion to the number of owners. So sales made in months after earlier sales periods will be reduced in value. The value of strategies that spread sales over long periods, including intertemporal price discrimination, will decline relative to the value of strategies that concentrate sales over smaller timescales. Selecting an optimal pricing strategy balances the returns from intertemporal price discrimination against the losses due to piracy. We can see the selection in figure 2.1. Price changes are increasingly concentrated over smaller periods and occur earlier. The timing of the compressed price changes is determined by the discounting which makes early sales more valuable to the legal seller than late sales.

2.5.2 Mean sales time

Figure 2.2: Mean sales time with fixed market size: time of launch (dots), mean sales time after launch (triangles), and total mean sales time (crosses) as functions of the piracy rate



With fixed market size and positive discounting, piracy leads to earlier price declines than under intertemporal price discrimination. Such pricing strategies accelerate sales. We can quantify the acceleration in response to piracy by examining the mean time for sales,

$$\sum_{t=1}^{T} tS_t / \sum_{t=1}^{T} S_t \tag{2.8}$$

where S_t are the total sales at time t. The formula only includes sales made during the product life. When sales satisfy all market demand, the mean times for sales and diffusion coincide. However, as we will shortly see instances in which diffusion is incomplete and the mean time for diffusion is infinite, we consider the mean time for sales instead.

The mean time for sales may be decomposed into time until product launch and mean sales time after launch, in the form

$$\sum_{t=1}^{T} (t-L)S_t / \sum_{t=1}^{T} S_t + L \tag{2.9}$$

where L is the launch time, that is, the first period of sales.

We calculate the launch time and post-launch mean sales time for piracy rates between 0 and 0.0001. The results are shown in figure 2.2. The launch time is always the first month, so the total and post launch mean sales times are just shifted by a single month. They reduce sharply as the piracy rate rises a little, with a further reduction at a higher rate.

2.5.3 Welfare

We now examine welfare. We saw in the last subsection that in our model, sales are accelerated by piracy, so the value people derive from them should be discounted less and welfare should increase. The changing pricing strategy may also be expected to change the division of welfare between company and buyer. In this section, we examine how welfare is divided into profits, consumer surplus, and pirate charges. As it is assumed that profits and charges are net of production costs, pirate charges are surplus captured by producers of the pirate good. We could include non-zero and differential production costs in the model, but the analysis would move us away from timing issues in welfare and towards other theoretical mechanisms (Johnson, 1985; Besen, 1986; Belleflamme, 2002; Bae and Choi, 2006).

We have seen that the formula for a company's discounted profits is given by equation 2.7. The corresponding equation for acquisition charges from pirate sources is

$$\sum_{t=1}^{T} d^t \frac{k_t}{1+k_t} p(t) \sum_{m \in m_{p(t)}} C_m(t) \tag{2.10}$$

Then the total cost of adoption from any source is the sum of equations 2.7 and 2.10, or

$$\sum_{t=1}^{T} d^t \sum_{m \in m_{p(t)}} p(t) C_m(t) \tag{2.11}$$

The total gross value derived from adoption from either legal or pirate sources is the same as the total welfare. Sales occur for buyers with willingness to buy of $1-(m-0.5)/M$ if and only if $1-(m-0.5)/M \geq p(t)$. Thus, the formula for discounted total value derived from sales (and hence total welfare) is

$$\sum_{t=1}^{T} d^t \sum_{m \in m_{p(t)}} (1-(m-0.5)/M) C_m(t) \tag{2.12}$$

Total consumer surplus is the difference between total welfare in equation 2.12 and total acquisition costs in equation 2.11, or

$$\sum_{t=1}^{T} d^t \sum_{m \in m_{p(t)}} ((1 - (m - 0.5)/M) - p(t))C_m(t) \tag{2.13}$$

Figure 2.3: Welfare with fixed market size: consumer surplus (horizontal stripes), pirate charges (vertical stripes), and legal seller profits (slanting stripes) as functions of the piracy rate

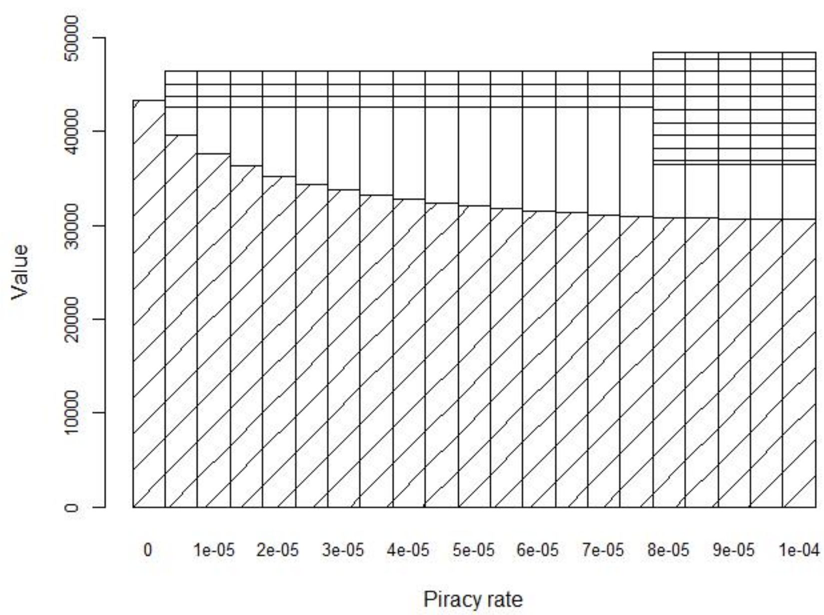


Figure 2.3 shows welfare and its components as a function of the piracy rate. As expected, total welfare rises as piracy does due to the reduced discounting. The welfare rise is much gentler than the decline in sales time, as most sales acceleration is to buyers with lower valuations. In the mean sales time calculation, only the number of sales matter, whereas in the welfare calculation the valuations are included.

Profits account for the entire surplus when piracy is zero as perfect skimming is practiced. When the piracy rate increases a little, profits drop sharply as companies begin to share our their profits with small number of pirate providers over most of their extended sales strategy. As the piracy rate rises, the number of pirating agents who share the income increases linearly, so the legal share declines in inverse proportion and by smaller amounts as the rate rises. Moreover, price changes are more compressed in time at the higher rates of piracy, so that increases in piracy act over small periods of time.

As the piracy rate rises from zero, pirate charges rapidly increase their share of total welfare. The rate of increase declines over time, and the share reaches its maximum value at a rate of 0.000075. A general small trend to increase persists thereafter. However, there is a large downward correction in the share of piracy as the rate reaches 0.00008, and as a result pirate charges are smaller when piracy rates are largest compared with more moderate rates.

At low levels of piracy, price adjustment is delayed because earlier adjustment reduces the extent of intertemporal price discrimination excessively. So piracy is present when prices are higher during the early skimming, and so pirate providers receive quite a large part of total welfare. As piracy increases, it becomes optimal for the legal seller to reduce prices earlier on, and so pirate providers capture lower shares of total welfare.

Consumer surplus is zero at the lowest rates of piracy. It increases by steps as the rate rises. At the higher rates of piracy it accounts for more than pirate charges, at around a quarter of profits. The behaviour may be explained by noting that when the piracy rate is low, perfect intertemporal price discrimination extracts all profits from consumers. The surplus extraction falls as the piracy rate increases and pricing strategy departs from skimming. The large departure from price discrimination that occurs at high piracy rates results in consumer surplus gains.

We summarise the preferences for piracy rates by the market participants when market size is fixed. Legal sellers prefer no piracy as they can extract the entire market surplus. Pirate providers prefer a moderately high rate where they can capture as much of the market as possible without triggering the legal seller to reduce prices too steeply and early, leaving the pirate providers with few and low valuing buyers. Consumers like piracy as high as possible because of the price reductions entailed by piracy prevention.

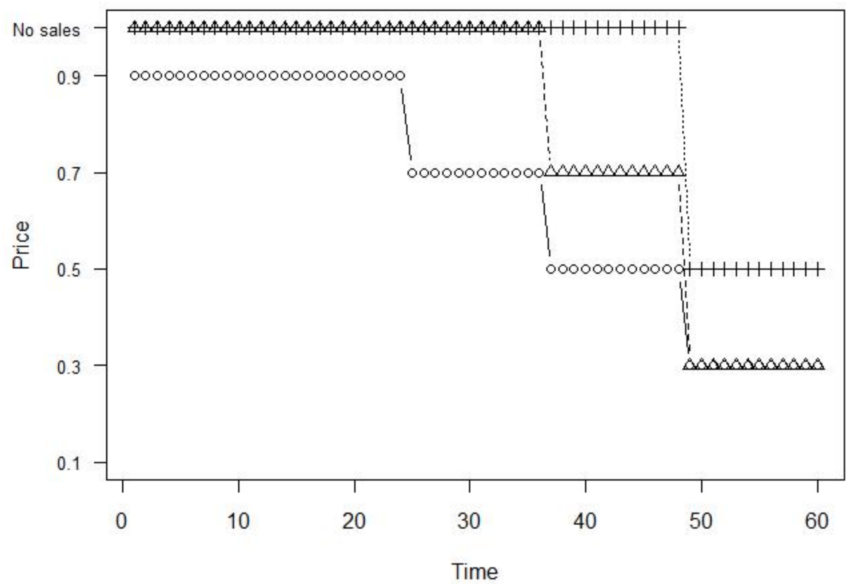
2.6 Welfare with market growth

2.6.1 Pricing

In this section, we examine pricing in the presence of piracy when market size starts at zero and increases by 1000 every month. Figure 2.4 shows the pricing strategy as the piracy rate rises. The circles show pricing when piracy is zero. Prices are held at the highest consumer valuation for two years. Then prices are reduced by three steps, from the highest valuation to the second lowest. The triangles show pricing at a higher piracy rate, so that there are pirate providers equivalent to $60 \times 1000 \times 0.00007 = 4.2$ legal sellers by the end of the product life. The pricing adjusts so that the legal seller delays its market entry until the start of the fourth year and then reduces its prices over two years. The crosses show pricing when piracy ends up equivalent to six legal sellers. The legal seller holds launch until the last year, and then puts prices at the third lowest valuation.

When there is no piracy, the explanation for the pricing is that the legal

Figure 2.4: Price variation as a function of the piracy rate when the market is growing. The rates are 0 (circles), 0.00007 (triangles), and 0.0001 (crosses).



seller attempts to extract as much available surplus as possible. In the first few years, they sell only at the top valuation price and so capture all surplus from the top valuers. As the market size is growing, the consumers in the top valuation band are replaced and surplus can continue being extracted from them. However, the number of consumers in lower valuation bands also grows and it enhances profits to sell to them after a time.

For non-zero piracy, the early sales increase the number of pirate providers who share later revenues. There is an increase in the value of strategies that compress price reductions relative to strategies that stagger them, which we again see in the graph with the compression becoming acuter as the piracy rate rises. The timing of the compression is due to the market growth. Early sales would capture little of the total market emergent over the whole product lifetime, but would expose the legal seller to piracy when market size is much larger. So it is optimal to delay the compression until later in the period, with the delay rising with the piracy rate.

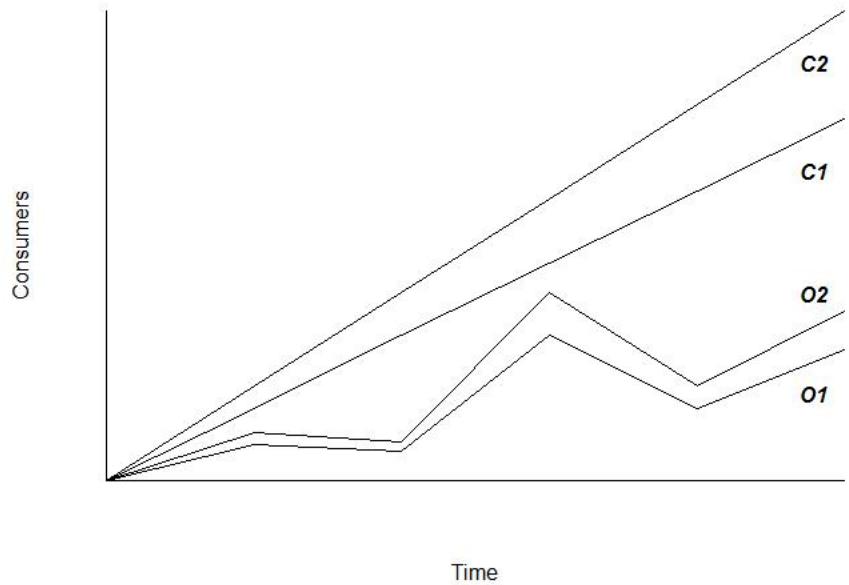
We can examine the relation between piracy and market growth by referring again to the legal seller's optimisation problem. A change in the constant market growth rate alters $n_m(t)$ to $bn_m(t)$ for some constant b and all t. Since the valuation bands evolve under $C_m(t+1) = n_m(t)$ if $1-(m-0.5)/M \geq p(t)$ and $C_m(t+1) = C_m(t) + n_m(t)$ otherwise, $C_m(t)$ is also scaled up by a factor of b for all t and m. Further, as pirate sales are proportional to past sales, $k_t = s\sum_{\tau=1}^{t-1}\sum_{m\in m_{p(\tau)}} C_m(\tau)$ and so k_t is also increased by a factor of b. Inserting these adjusted functional forms in maximised expression 2.7, we have

$$\sum_{t=1}^{T} \frac{d^t}{1+bs\sum_{\tau=1}^{t-1}\sum_{m\in m_{p(\tau)}} C_m(\tau)} p(t)b \sum_{m\in m_{p(t)}} C_m(t) \tag{2.14}$$

The b multiplying the fraction can be factored out of the objective function entirely and so does not affect decision making. Thus, the effect of a change in the constant growth rate on diffusion is the same as a change in the piracy rate, up to a rescaling of the diffusion curve.

Another way of expressing the result is that piracy is a share of past sales, so the effect on piracy of a scaling in sales is equivalent to an increase in the share of pirate sales out of past sales. All income is directly rescaled by the same factor, so doesn't affect the legal seller's decision making. Thus, a rescaled market growth is equivalent to a piracy rate change for decision making, and an equivalent rescaling for the overall income. The result is

Figure 2.5: Optimal sales paths for market size emergence curves. Sales path $\boldsymbol{O1}$ corresponds to market size emergence curve $\boldsymbol{C1}$, and $\boldsymbol{O2}$ $(= b \times \boldsymbol{O1})$ corresponds to market size emergence curve $\boldsymbol{C2}$ $(= b \times \boldsymbol{C1})$. The piracy rate for the second curve is b times lower than for the first curve.



shown graphically in figure 2.5 [2]. Curve $\boldsymbol{C1}$ traces total market size at one rate of growth and curve $\boldsymbol{C2}$ traces market size emerging at a rate b times higher. The sales path $\boldsymbol{O1}$ is optimal out of many possible paths, with the sum of points on the path giving the sales path's value to the company. Rescaling piracy by $1/b$ and increasing market size by a factor of b maps the set of possible sales paths for $\boldsymbol{C1}$ to the set for $\boldsymbol{C2}$. Thus, the optimal sales path $\boldsymbol{O2}$ is just the optimal sales path $\boldsymbol{O1}$ scaled upwards by b at the revised piracy rate.

[2] Thanks to Paul Fenn for suggesting a graphical interpretation.

2.6.2 Mean sales time

Figure 2.6: Mean sales time when the market is growing: time of launch (dots), mean sales time after launch (triangles), and total mean sales time (crosses) as functions of the piracy rate

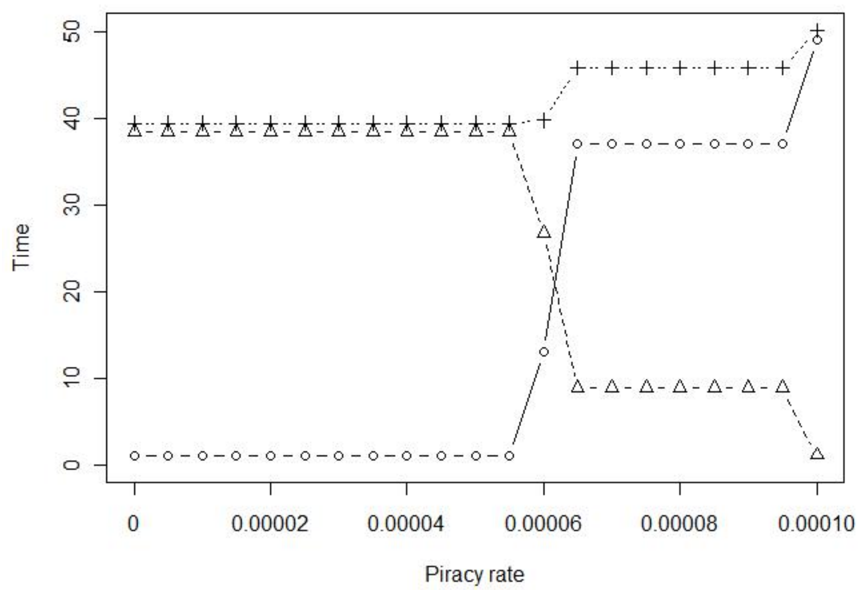


Figure 2.6 shows the mean total sales time as a function of the piracy rate, divided into the time until launch and mean sales time after launch. The total sales time initially does not change with a rising piracy rate, but then undergoes small jump increases as the market entry date shifts backwards. The launch date is delayed heavily by rises in the piracy rate. Its movement alternates between large jumps and long periods of no change. The post-launch mean sales time displays the opposite movement. There is initially a long sales time, but the time falls to almost zero at the maximum

piracy rate.

When we examined sales times for the fixed market size, the post-launch sales time also declined with rising piracy. However, the launch time remained the same for all piracy rates, in contrast to the results for the increasing market size here. The differences in launch time explain the divergent findings on mean total sales time.

2.6.3 Welfare

Figure 2.7: Welfare when the market is growing: consumer surplus (horizontal stripes), pirate charges (vertical stripes), and legal seller profits (slanting stripes) as functions of the piracy rate

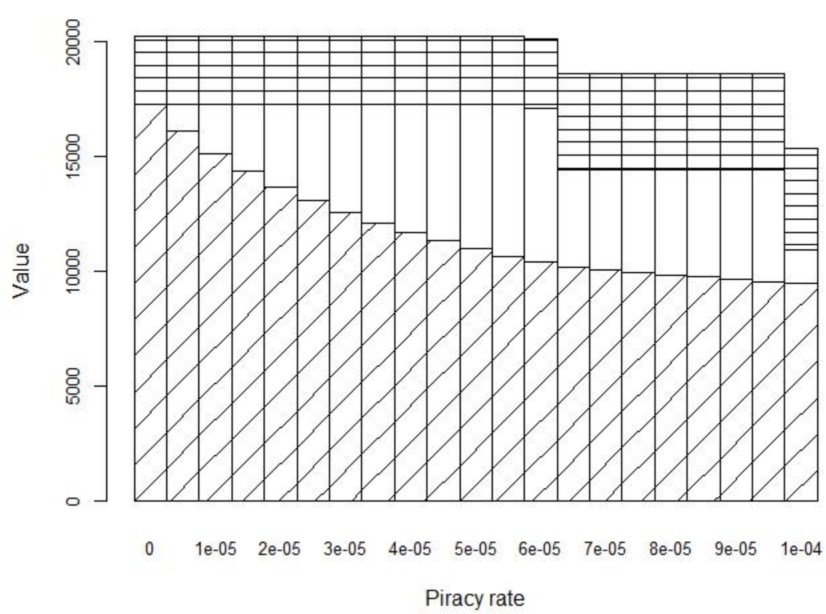


Figure 2.7 shows total welfare as a function of the piracy rate, decom-

posed into consumer surplus, pirate charges, and legal seller profits. The total welfare declines over time, with one very minor decline in welfare (at a rate of 0.00006) and two larger ones. Welfare is unchanging for most rates. Company profits decline rapidly when the piracy rate first starts to increase before the decline slows, as profits are inversely related to the number of pirating agents.

Pirate charges are subject to a general increase that is initially rapid and then slows, as the rate of substitution for legal sales declines. However, pirate charges undergo downward revisions of increasing magnitude as the piracy rate increases, with the final revision eradicating most of the pirate charges. The declines are due to compression of price changes and truncation of sales at the end of the product life.

Consumer surplus does not change as the piracy rate rises through low and moderate levels. As the rate rises a little further, there is a large increase in welfare as price changes are compressed and more surplus is transferred from providers to buyers. The piracy rate then increases again without any change in surplus, before surplus increases slightly at the highest piracy rate. The surplus increase is a result of two effects: an additional delay leading to increased discounting and reduced consumer surplus, and reduced skimming and surplus extraction by companies. The latter effect is the dominant one.

We can again order the preferences for piracy of the market participants based on the welfare they derive. The legal seller prefers no piracy while pirate providers prefer a moderate rate, but do badly at very high rates. Consumers like high piracy rates. Preferences for small changes in piracy rates depend on the current rate. At low rates, it is in the interest of pirate providers to increase rates but against the interest of legal sellers. At two particular rates, consumers benefit from small increases in the rate but pirate providers suffer, but usually consumers are indifferent to the increase and pirate providers benefit.

Our model identifies a dynamic welfare trade-off due to piracy. Total welfare increases with the piracy rate when market size is constant, while it declines with the piracy rate when market size is rising. The different welfare outcomes indicate the presence of two competing mechanisms that are differentially activated by the rate of market growth. On one hand, piracy induces compression of price changes that accelerates sales and increases welfare. On the other hand, piracy increases the product launch delay in the presence of market growth, so decelerating sales. If the piracy rate or market growth are very high, product launch may be so delayed that some consumers who would have otherwise purchased it do not buy the product before it becomes obsolescent.

2.7 Conclusion

In this paper, we have specified a model of pricing in the presence of piracy and with heterogeneous consumers. Piracy is found to lower the profitability of a skimming strategy in favour of a compressed price reduction scheme. With a fixed market size, piracy increases welfare but in a growing market it reduces welfare. The optimal piracy rate choices of consumers, pirate providers, and legal sellers do not generally coincide.

Piracy is found to trade off two effects on sales time and welfare in the presence of market growth, by both delaying product launch and accelerating subsequent sales. Further work could clarify the mechanisms algebraically and classify them among other possible ones with related impact.

Among the possible modifications could be allowance of a role for information spreading as in Givon *et al.* (1995), consideration of the impact of partial transfer of product value forward after the end of its lifetime, and inclusion of incentives to innovate (see Jaisingh (2009), Banerjee and Chatterjee (2010), and Banerjee (2013)).

We have not discussed here how varying the fixed parameters would change our results. In the working paper version of this document (Waters, 2014), we show that purchase delay mitigates the effect of piracy while rising demand elasticity increases it. Transient heterogeneity renders pricing immune to piracy's impact while even low network demand externalities reduce the impact. Piracy continues to delay product launch if market growth is subject to uncertainty. Greater elasticity of piracy with respect to past sales increases piracy's effect. Future work could examine the effect of these influences in more detail.

Pirate providers have been assumed to follow the pricing of the legal seller, after adjustment for different quality of the pirate copy. An alternative assumption would be to allow for strategic competition between the legal seller and pirate providers (see Jaisingh (2009)). As the strategy would give rise to a repeated game where the number of players at each stage is dynamic, the solution is likely to be complicated and have multiple equilibria. In some strategies, existing pirate providers may cooperate with the legal seller to slow down pirate entry in order to prevent their income being reduced by new pirate providers.

Instead of our assumption of a single legal seller, we could alternatively introduce multiple legal sellers (as in Minniti and Vergari (2010), for example). If they are assumed to compete strategically, a repeated game would again emerge with a dynamic number of players, as with similar behaviour by pirate providers. The outcomes could be analysed in future research. An alternative assumption is that the other legal sellers follow the pricing of the original seller. The effect of piracy on pricing would be mitigated relative to the case with a single legal seller, because the percentage decline in the revenue per legal seller due to extra pirate sellers would be much smaller. So skimming would be expected to be practiced to a greater extent rather than compression and delay in pricing to avoid piracy's impact.

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Chapter 3

The influence of information sources on initial technology adoption and intensification: evidence from UK farming

3.1 Introduction

Initial technology adoption is the first use of a technology by a company and when it occurs over time describes the inter-firm diffusion of a technology between companies. Intensification is the extent of a technology's use by a company, and its process over time traces intra-firm diffusion 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 determinants driving intensification by contrast with the more extensively investigated initial adoption.

A determinant that has attracted the attention of researchers is information acquisition. 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 intensification emphasise how information acquisition can explain diffusion (Mansfield, 1968; Stoneman, 1981), and the potential role of learning is recognised in the empirical intensification literature even when it is not a primary concern (Battisti and Stoneman, 2005).

The agricultural economics literature has examined in some detail how information affects adoption, 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; Läpple 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 initial adoption and intensification. In this paper, we examine the comparative impact of information sources on initial adoption and intensification 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. The model has similarities to Tonks (1983) in presenting a finite horizon model of learning and adoption, but whereas in Tonks (1983) learning occurs through technology acquisition, in our model learning happens when information is purchased separately. The model describes sequential acquisition of information and a technology by a company. The company can use exploratory information to reduce uncertainty about the technology's performance, or technical information to increase the performance.

Our model implies that different sources of information will be influential at the initial adoption and intensification stages. In initial adoption, information's value arises from revealing profitable opportunities from undertaking a technological trial. As the value is expected to be low, 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 land agents, farmers, and agricultural magazines will be influential on initial adoption.

For intensification, 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 intensification over an inexpensive source that does not add value. Such value-creating sources plausibly include buyers, consultants, academics, and government.

We test our model using a cross section of 574 UK farmers surveyed in 2007, looking at the extent of their adoption of organic farming techniques. 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 initial adoption and intensification broadly hold. Specifically, we find that information from agents, farmers, and agricultural magazines is mainly influential on initial adoption. Information from academics is largely used for intensification, while information from crop consultants, suppliers, and buyers is used for both. Government information is more associated with intensification, compared with our expectation of dual use.

Our theoretical contribution is to present a model of what type of information influences initial technology adoption and what type influences intensification. The model allows prediction of the disaggregated information sources used in technological adoption, and it demonstrates qualitative differences in information sources used in the two diffusion stages. Erdem et al (2005) also distinguish between the effect of different types of information on adoption, but look at consumer choice of goods, rather than initial adoption and intensification by companies. Our model produces results similar to those in dual process persuasion theory (Petty and Cacioppo, 1986; Chaiken, 1980; Kruglanski and Thompson, 1999), where information with low processing requirements is used when there is little personal involvement in a subject and information with high processing requirements is used when there is high involvement. Unlike related 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.

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

Section 3.2 looks at our theoretical framework and section 3.3 describes our data. Section 3.4 classifies our information sources, section 3.5 presents our estimation procedure, results are in section 3.6, and section 3.7 concludes.

3.2 Theoretical framework

In this section we present our model of joint information and technology usage, in which a company can adopt a new technology with uncertain performance. There are two types of information available to purchase. The first is exploratory and reduces uncertainty about the returns available from using a new technology, while the second type is technical and raises those returns. The company's learning follows Bayesian updating, as is common in the literature (Aldana et al, 2011; Baerenklau, 2005; Bandiera and Rasul, 2006; Conley and Udry, 2001; Foster and Rosenzweig, 1995; Grossman et al, 1977; Leathers and Smale. 1991; Kihlstrom, 1976; Stoneman, 1981; Young, 2009). We show that the first type of information is associated with technology trial, while the second type is associated with increased technology use. We then classify the information sources used in our UK data according to whether they are exploratory, technical, or both. The model results are then applied to state whether the sources will be more influential on initial adoption, intensification, or both.

Our model is similar to that proposed by Tonks (1983), which is also a finite horizon model with learning about an uncertain technology. There are significant differences between the models, however. Tonks (1983) has learning occurring when the technology is adopted, whereas in this chapter technology and knowledge acquisition are separated. In Tonks (1983), information has a single function of reducing uncertainty about the technology's performance, whereas in our model information can also improve performance.

3.2.1 Model

3.2.1.1 Specification

There is a risk neutral, profit maximising company which can invest in a new technology to replace a current technology. Replacement can be partial or complete. If the company adopts K units of the technology, then the additional income relative to the income from the existing technology is $K^{\alpha}H\varepsilon$, where H measures the effect of the skill of use, ε is a stochastic term capturing other influences on income, and α is a constant satisfying $1 > \alpha > 0$. Income follows in the period after investment. The cost of the technology is a constant k per unit.

The effect of skill of use, H, is assumed to depend on the amount of technical information, J, that the company has. Technical information is assumed to exhibit diminishing marginal returns, in the form $H = J^{\gamma}$ if $\varepsilon > 0$ for some constant γ satisfying $1 - \alpha > \gamma > 0$. This condition ensures net income has a finite solution for K and J. When $\varepsilon \leq 0$, $H = 0$ so that the outcome of using the new technology is no worse than for the old technology. The company chooses the amount J of technical information to use at a constant cost of j per unit, and is effective from the period after its acquisition.

The stochastic term ε has a normal distribution $f(\varepsilon)$ with mean z and standard deviation σ_f. The company is unaware of the value of z, and assumes that it has a normal prior stochastic distribution $g(z)$, with mean $\mu_g << 0$ and the standard deviation $\sigma_g << -\mu_g$ where << means "much less than". Exploratory information can be used to revise the estimate of z, with each piece of exploratory information ε_i being an independent sample of ε. The company updates its subjective distribution of z by conditioning on the observations, and updating is effective in the period after investment. The company chooses the number of pieces I of exploratory information to use at a price of i per unit. Total expenditure iI on exploratory information always remains much smaller than the total budget available to the company.

Prior to any investment, the company undertakes a trial of the technology, which is its initial adoption. The dummy T takes the value 1 if a trial occurs and 0 otherwise. The trial has a cost of t and reveals the value of z in the following period.

Companies have an initial budget of M which is not exogenously increased at later dates. The cost of a trial is smaller than the budget, so $tT < M$. Funds accumulate at the discount rate on future revenue, and all prices increase at the same rate, so that the timing of investment decisions does not affect their value. The company chooses its acquisitions of technology, and technical and exploratory information, over three periods.

Denoting the value to the company by *V*, and letting suffixes indicate the time at which quantities are evaluated, the company solves the following maximisation problem in the first period:

$$E(V_1) = \max_I (E(V_2 \mid I))$$

where $iI \le M$, while in the second period they solve

$$E(V_2 \mid I) = \max_T (E(V_3 \mid I, T))$$

where $tT \le M - iI$, and in the third period they solve

$$E(V_3 \mid I, T) = \max_{J,K} (M - iI - tT - jJ - kK + zJ^{\alpha} K^{\gamma}) .$$

where $jJ + kK \le M - iI - tT$

For notational clarity, we have not included the possibility of investment in the first period without any prior exploratory information. We shall shortly show that without any prior information, investment in the second period does not occur, and the same logic applies to investment in the first period. We have also excluded the possibility of use of information after investment has occurred, or use of exploratory information after a trial has occurred. In our model, these uses only decrease value to the company. The reasons are that if technical information increased profit from investment, it could be more profitably used at the time of investment, while if exploratory information is used after a trial, it is not revealing any information not already revealed by the trial.

The model does not seem readily to take the form of a compact real options problem, but can be expressed in a real options framework in a more diffuse way. The trial is like an asset with a stochastic distribution of outcomes. Deciding on whether to undertake a trial without information can be considered as deciding irrevocably whether to acquire the asset prior to the date its value is known for sure. Deciding on whether to undertake the trial when the company has perfect information is like purchasing an option to buy the asset when its value is revealed. Deciding on whether to undertake the trial when the company has partial information is like purchasing an option to buy the asset when its value is quite certain. Pricing and comparing each of these options using real options techniques could be an alternative method of analysis to the one we present, but doesn't seem to be any shorter.

Our theoretical model considers the information acquisition choices of a single company, without explicit allowance for competition in acquisition or use of information or technology. As we aim to highlight the different adoption outcomes that arise from two learning mechanisms, we consider it reasonable not to include competition explicitly. If we assumed copycat behaviour from other companies then we could allow for their involvement by making more severe the diminishing returns from information use (due to higher costs); diminishing returns are already an assumption for technical information and, we shall show, a consequence of our formulation for exploratory information. Alternatively strategic behaviour could be assumed (as in Reinganum (1981) for example), which would potentially have multiple simultaneously played games. We allow for local word of mouth effects in the empirical specification, and consider other forms of interaction between adopters and potential adopters in the conclusion.

3.2.1.2 Solution

We solve the problems backward. We first consider the case when no prior exploratory information occurs. The third period maximisation is

$$E(V_3 \mid I=0,T) = \max_{J,K}(M - tT - jJ - kK + zJ^{\alpha}K^{\gamma}),$$

which implies an optimal income following from a trial of $zJ^{\alpha}K^{\gamma} - jJ - kK$. If $z < 0$ then clearly it is optimal to set $J = K = 0$ and no investment occurs. The trial reveals the value of *z*, and is expected to be drawn from the prior distribution $g(z)$. The expected optimal income from a trial is thus

$$\begin{aligned}
EV_2 &= \int_0^{\infty}(zJ^{\alpha}K^{\gamma} - jJ - kK)g(z)dz + \int_{-\infty}^{0} 0g(z)dz \\
&= \int_0^{\infty}(zJ^{\alpha}K^{\gamma} - jJ - kK)g(z)dz \\
&\leq \int_0^{\infty} zJ^{\alpha}K^{\gamma}g(z)dz \\
&\leq \max(J^{\alpha}K^{\gamma})\int_0^{\infty} zg(z)dz \\
&= \max(J^{\alpha}K^{\gamma})\int_0^{\infty}\frac{z}{\sqrt{2\pi\sigma_g{}^2}}\exp\left(-\left(\frac{z-\mu_g}{2\sigma_g}\right)^2\right)dz \\
&= \max(J^{\alpha}K^{\gamma})\int_{-\mu_g/\sigma_g}^{\infty}\frac{y+\mu_g/\sigma_g}{\sqrt{2\pi\sigma_g{}^2}}\exp\left(-\left(\frac{y}{2}\right)^2\right)dy
\end{aligned}$$

The last expression uses the substitution $y = (y - \mu_g)/\sigma_g$. Since by assumption $\sigma_g << -\mu_g$, the lower limit is large. The exponential term converges to zero as $y \to \infty$ faster than any power of *y* and in particular faster than y^{-3}. Given the lower limit and the region of integration, we have

$$
\begin{aligned}
EV_2 &\le \max(J^\alpha K^\gamma)\int_{-\mu_g/\sigma_g}^{\infty} \frac{y+\mu_g/\sigma_g}{\sqrt{2\pi\sigma_g{}^2}} \exp\left(-\left(\frac{y}{2}\right)^2\right) dy \\
&\le \max(J^\alpha K^\gamma)\int_{-\mu_g/\sigma_g}^{\infty} \frac{y+\mu_g/\sigma_g}{\sqrt{2\pi\sigma_g{}^2}} \left(\frac{y}{2}\right)^{-3} dy \\
&= \frac{4\max(J^\alpha K^\gamma)}{\sqrt{2\pi\sigma_g{}^2}} \int_{-\mu_g/\sigma_g}^{\infty} y^{-2} + (\mu_g/\sigma_g) y^{-3} dy \\
&= \frac{4\max(J^\alpha K^\gamma)}{\sqrt{2\pi\sigma_g{}^2}} [y^{-1} + (\mu_g/2\sigma_g) y^{-2}]_{\infty}^{-\mu_g/\sigma_g} \\
&= \frac{8\max(J^\alpha K^\gamma)}{\sqrt{2\pi\sigma_g{}^2}} \frac{1}{-\mu_g/\sigma_g}
\end{aligned}
$$

which is small since $1 << -\mu_g/\sigma_g$. On the other hand, the cost t of a trial is not. Thus, in the absence of exploratory information, no trial is undertaken. If a company doesn't expect a technology to offer them any benefits – for example if the company isn't even aware of its potential in production – then it will not bother to undertake a trial.

Our proof depends on the normal distribution of z. For greater breadth, it would be preferable to use a general distribution function. We attempted to use Chebyshev's inequality to prove the result with such a function, only relying on the assumptions about the mean and standard deviation of z. However, we could not immediately do so, and therefore cannot rule out the presence of a (perhaps pathological) distribution which would violate our result.

We next turn to the case when explanatory information may be used. The final period problem is to maximise

$$E(V_3 \mid I,T) = M - iI - tT - jJ - kK + zJ^\alpha K^\gamma. \tag{3.1}$$

over J and K, taking I and T as given and subject to the budget constraint $jJ + kK \le M - iI - tT$. We also have $J \ge 0$ and $K \ge 0$. If either J or K is zero, the other is too. We focus on behaviour when they are non-zero. The Lagrangian for minimisation is then

$$L = -M + iI + tT + jJ + kK - zJ^{\alpha}K^{\gamma} + \lambda(jJ + kK - M + iI + tT)$$

We first consider the situation where the budget condition is binding, so $\lambda \neq 0$. The first order conditions are

$$j - \alpha z J^{\alpha-1}K^{\gamma} + \lambda j = 0 \tag{3.2}$$

$$k - \gamma z J^{\alpha}K^{\gamma-1} + \lambda k = 0$$

and

$$jJ + kK - M + iI + tT = 0 \tag{3.3}$$

We multiply equation (3.2) by J to get

$$(1+\lambda)jJ - \alpha z J^{\alpha}K^{\gamma} = 0 \tag{3.4}$$

and the second equation is multiplied by K to get

$$(1+\lambda)kK - \gamma z J^{\alpha}K^{\gamma} = 0$$

or

$$\frac{(1+\lambda)k}{\gamma z}K = J^{\alpha}K^{\gamma} \tag{3.5}$$

Substituting from equation (3.5) in equation (3.4) we have

$$(1+\lambda)jJ - \alpha z\frac{(1+\lambda)k}{\gamma z}K = 0$$

or

$$J = \frac{\alpha k}{\gamma j} K$$

Since all parameters on the right hand side are positive, there is a positive linear relation between the amount of technical information used and the amount of technology purchased.

Substituting for J in equation (3.3) gives

$$j \frac{\alpha k}{\gamma j} K + kK - M + iI + tT = 0$$

or

$$K = \frac{\gamma(M - iI - tT)}{k(\gamma + \alpha)}$$

Thus, conditional on investment occurring and the budget being spent in full, the amount K of capital used has a negative linear relation with the amount I of initial exploratory information used.

We also have the amount of technical information used:

$$J = \frac{\alpha(M - iI - tT)}{j(\gamma + \alpha)}.$$

Equation (3.2) can be rearranged to give

$$\lambda = -1 + \frac{\alpha z}{j} J^{\alpha - 1} K^{\gamma}$$

Substituting for *J* and *K* gives

$$\lambda = -1 + \frac{\alpha z}{j}\left(\frac{\alpha(M - iI - tT)}{j(\gamma+\alpha)}\right)^{\alpha-1}\left(\frac{\gamma(M - iI - tT)}{k(\gamma+\alpha)}\right)^{\gamma}$$

or

$$\lambda = -1 + \frac{\alpha z}{j}\left(\frac{\alpha}{j}\right)^{\alpha-1}\left(\frac{M - iI - tT}{\gamma+\alpha}\right)^{\alpha-1}\left(\frac{\gamma}{k}\right)^{\gamma}\left(\frac{M - iI - tT}{\gamma+\alpha}\right)^{\gamma}$$

or

$$\lambda = -1 + z\left(\frac{\alpha}{j}\right)^{\alpha}\left(\frac{\gamma}{k}\right)^{\gamma}\left(\frac{M - iI - tT}{\gamma+\alpha}\right)^{\alpha+\gamma-1}$$

To meet the Kuhn-Tucker conditions, we must have $\lambda > 0$, and so

$$z > \left(\frac{j}{\alpha}\right)^{\alpha}\left(\frac{k}{\gamma}\right)^{\gamma}\left(\frac{\gamma+\alpha}{M - iI - tT}\right)^{\alpha+\gamma-1}$$

This may be read as a condition on the minimum income required for investment when the budget condition is binding. The objective function in equation (3.1) has second derivatives given by

$$d^2F/dI^2 = \gamma(\gamma-1)zJ^{\alpha}K^{\gamma-2}$$

$$d^2F/dJ^2 = \alpha(\alpha-1)zJ^{\alpha-2}K^{\gamma}$$

and

$$d^2F/dIdJ = \gamma\alpha zJ^{\alpha-1}K^{\gamma-1}$$

So the determinant of the Hessian is

$$(d^2F/dI^2)(d^2F/dJ^2)-(d^2F/dIdJ)^2$$
$$=\gamma(\gamma-1)zJ^{\alpha}K^{\gamma-2}\alpha(\alpha-1)zJ^{\alpha-2}K^{\gamma}-(\gamma\alpha zJ^{\alpha-1}K^{\gamma-1})^2$$

or

$$(d^2F/dI^2)(d^2F/dJ^2)-(d^2F/dIdJ)^2$$
$$=(\alpha-1)(\gamma-1)\alpha\gamma z^2J^{2\alpha-2}K^{2\gamma-2}-\alpha^2\gamma^2z^2J^{2\alpha-2}K^{2\gamma-2}$$

or

$$(d^2F/dI^2)(d^2F/dJ^2)-(d^2F/dIdJ)^2=(1-\alpha-\gamma)\alpha\gamma z^2J^{2\alpha-2}K^{2\gamma-2}>0$$

We also have the trace

$$d^2F/dI^2+d^2F/dJ^2=\gamma(\gamma-1)zJ^{\alpha}K^{\gamma-2}+\alpha(\alpha-1)zJ^{\alpha-2}K^{\gamma}<0$$

Thus, the extremum is a local maximum.

We next consider the case where the budget condition is not binding, so $\lambda=0$. The first order conditions are

$$j-\alpha zJ^{\alpha-1}K^{\gamma}=0 \tag{3.6}$$

and

$$k-\gamma zJ^{\alpha}K^{\gamma-1}=0$$

The first equation implies

$$\alpha zJ^{\alpha}K^{\gamma}=jJ \tag{3.7}$$

The second equation implies

$$\frac{k}{\gamma z}K = J^{\alpha}K^{\gamma} \tag{3.8}$$

Substituting equation (3.8) in equation (3.7) gives

$$\frac{\alpha k}{\gamma j}K = J \tag{3.9}$$

as earlier. There is a positive linear relation between technology and information acquisition. Substituting back into equation (3.6) gives

$$j - \alpha z\left(\frac{\alpha k}{\gamma j}K\right)^{\alpha-1}K^{\gamma} = 0$$

or

$$K = \left(\frac{1}{z}\right)^{1/(\alpha+\gamma-1)}\left(\frac{j}{\alpha}\right)^{\alpha/(\alpha+\gamma-1)}\left(\frac{\gamma}{k}\right)^{(\alpha-1)/(\alpha+\gamma-1)}$$

Substituting back into equation (3.9) gives

$$J = \frac{\alpha k}{\gamma j}\left(\frac{1}{z}\right)^{1/(\alpha+\gamma-1)}\left(\frac{j}{\alpha}\right)^{\alpha/(\alpha+\gamma-1)}\left(\frac{\gamma}{k}\right)^{(\alpha-1)/(\alpha+\gamma-1)}$$

or

$$J = \left(\frac{1}{z}\right)^{1/(\alpha+\gamma-1)}\left(\frac{\alpha}{j}\right)^{(\gamma-1)/(\alpha+\gamma-1)}\left(\frac{\gamma}{k}\right)^{\gamma/(\alpha+\gamma-1)}$$

When income derived from technological investment is low so that investment is low and the budget constraint is not reached, there isn't any relation between expenditure on exploratory information and technology purchase conditional on investment occurring. We have also seen that conditional on investment occurring and the budget being spent in full, the amount *K* of capital used has a negative linear relation with the amount *I* of initial exploratory information used. However, we cannot say that the unconditional relationship is negative, because exploratory information also influences the decision for invest, which we address shortly.

We next treat the second period problem of deciding whether to undertake a trial. A trial reveals the value of *z*, allowing the optimal *J* and *K* to be chosen with the resulting income of $M - iI - tT - jJ - kK + zJ^{\alpha}K^{\gamma}$. The distribution of the variable *z* conditional on *I* pieces of exploratory information $\varepsilon_1, \ldots, \varepsilon_I$ is $g(z \mid \varepsilon_1,...,\varepsilon_I)$, and the expected gross value from a trial weights the gross income by the probabilities, so

$$\begin{aligned} &E(V_2 \mid I, T = 1) \\ &= \int_{-\infty}^{\infty} (M - iI - t - jJ(z) - kK(z) + zJ(z)^{\alpha} K(z)^{\gamma}) g(z \mid \varepsilon_1,...,\varepsilon_I) dz \end{aligned} \tag{3.10}$$

where we have made explicit the dependence of *J* and *K* on *z*. A trial will be taken if this expected value exceeds the value without a trial, which is

$$E(V_2 \mid I, T = 0) = \int_{-\infty}^{\infty} (M - iI) g(z \mid \varepsilon_1,...,\varepsilon_I) dz \,. \tag{3.11}$$

Thus we have the following solution for the decision variable *T*:

$$T = 1 \quad \text{if} \int_{-\infty}^{\infty} (zJ(z)^{\alpha} K(z)^{\gamma} - jJ(z) - kK(z)) g(z \mid \varepsilon_1,...,\varepsilon_I) dz > t$$

$$T = 0 \quad \text{otherwise.}$$

If $T = 1$, then the expected value created by the trial is

$$\int_{-\infty}^{\infty}(zJ(z)^{\alpha}K(z)^{\gamma}-jJ(z)-kK(z))g(z\mid\varepsilon_1,\ldots,\varepsilon_I)dz-t\,.$$

In the first period, the company decides how much exploratory information they wish to acquire. At the start of the first period, the value of a trial conditional on I pieces of unknown exploratory information $\varepsilon_1, \ldots, \varepsilon_I$ is the stochastic quantity $E(V_2 \mid I)$. Using the law of total expectation we can express the quantity's relation to a further, unknown piece of information ε_{I+1} in the form

$$E(V_2 \mid I)=\int_{-\infty}^{\infty}E(V_2 \mid I,\varepsilon_{I+1})f(\varepsilon_{I+1})d\varepsilon_{I+1}$$

The value $E(V_2 \mid I,\varepsilon_{I+1})$ is the expected value of the trial choice conditioned on the I pieces of exploratory information and additionally the I+1th piece of information ε_{I+1}.

The regions Ω and $\sim\Omega$ are defined as follows. The region Ω is the set of values of ε_{n+1} conditional on which a trial occurs (so a trial would have a positive expected value), and the region $\sim\Omega$ is the set of values of ε_{n+1} where a trial does not occur (so a trial would have a non-positive expected value). We separate the value of the trial into sub-integrals over these complementary regions:

$$E(V_2 \mid I)=\int_{\Omega}E(V_2 \mid I,\varepsilon_{I+1})f(\varepsilon_{I+1})d\varepsilon_{I+1}+\int_{\sim\Omega}E(V_2 \mid I,\varepsilon_{I+1})f(\varepsilon_{I+1})d\varepsilon_{I+1}$$

If the additional information ε_{I+1} is costlessly revealed, the company rejects the trial over the values of ε_{I+1} where the trial value is below t, so that the expected value from a trial is the first integral alone. If the company's decision in the absence of the additional information was to reject the trial, and if there exist values of ε_{I+1} where the value of the trial exceeds its cost, then the first integral is positive and information increases value. Similarly, if the company's initial decision was to pursue the trial, and if there exist values of ε_{I+1} where the value of the trial is below its cost, then the second integral is negative and information again increases value.

From inspections of equations (3.10) and (3.11), to calculate $E(V_2 \mid I)$ and $E(V_2 \mid I, \varepsilon_{I+1})$ require the calculation of the expressions $g(z \mid \varepsilon_1,...,\varepsilon_I)$ and $g(z \mid \varepsilon_1,...,\varepsilon_{I+1})$. We use Bayes' formula to do so. The distribution *g*(*z*) is $N(\mu_g, \sigma_g)$, while the distribution of the average $\bar{\varepsilon}$ of ε_1, …, ε_I is $N(z, \sigma_f / I)$. The average is a sufficient statistic for Bayesian updating of normal-normal distributions. The posterior $g(z \mid \varepsilon_1,...,\varepsilon_I)$ is then distributed $N(\mu_g{}^P, \sigma_g{}^P)$ where $\mu_g{}^P = \dfrac{\mu_g / \sigma_g + I\bar{\varepsilon} / \sigma_f}{1/\sigma_g + I / \sigma_f}$ and $\sigma_g{}^P = \dfrac{1}{1/\sigma_g + I/\sigma_f}$. As $I \to \infty$, $\mu_g{}^P \to \bar{\varepsilon}$ (which is itself convergent by the law of large numbers) and $\sigma_g \to 0$. Thus, increasing *I* has a diminishing expected effect on the conditional distribution of *g*(*z*), and hence on the conditional distribution of $E(V_2)$. If the distribution of $E(V_2 \mid I)$ doesn't change much in response to updating with ε_{I+1} then the integrated term $E(V_2 \mid I, \varepsilon_{I+1})$ will be close in value to $E(V_2 \mid I)$ with high probability. Consequently, if a trial is performed (respectively, not performed) with the initial information, it will tend to be performed (or not performed) with the extra information and the value gain from the information is low. We have used normality of our distributions to obtain these results, but again a distribution free proof would be preferable.

As the information ε_{I+1} is revealed at a constant cost of *i*, the act of disclosure also changes the value of $E(V_2 \mid I, \varepsilon_{I+1})$ by altering the value of the budget available for investment. As by assumption the total expenditure on exploratory information *iI* is small compared to the total budget, equations (3.10) and (3.11) show using one further piece of exploratory information has a limited effect on $E(V_2 \mid I, \varepsilon_{I+1})$. Exploratory information will be used up to the point at which its declining marginal value from disclosing the distribution of z equals the value of holding on to the funds for later.

Exploratory information therefore has two effects on the amount of technology used. On one hand, it reduces the amount of funds available to purchase the technology (or technical information). However, since the cost of exploratory information is assumed to be much smaller than the total budget available to the company, the effect is minimal. On the other hand, it increases the likelihood of a trial, and therefore any technology (or technical information) being used. The value of z to which the sample mean $\bar{\varepsilon}$ will converge is stochastic with distribution $f(\mu_g, \sigma_g)$, and so use of exploratory information leaves the value of z largely undetermined, conditional on a trial occurring. Since z is the determinant of the amount K of technology used, we can deduce that there is only a weak statistical association between exploratory information and intensification, whether that association is positive or negative in sign. We combine with the earlier finding on the positive relation between technical information and intensification to give a hypothesis in relative terms:

Hypothesis 1: intensification of technology usage has a stronger statistical relation (whether positive or negative) with technical information than exploratory information.

We can similarly observe that, given the level of exploratory investment, the occurrence of a trial indicates that the mean of the posterior distribution of z exceeds a threshold, but leaves the precise value of z uncertain. z is the determinant of the technical information usage J, so only a weak statistical association exists between technical information and initial adoption. Combining with the previous finding on the relation between exploratory information and initial adoption, the following relative hypothesis arises:

Hypothesis 2: initial technology adoption has a stronger statistical relation (whether positive or negative) with exploratory information than technical information.

3.3 Data

The main data used in this study is from a survey of pest management practices by UK farmers (Bailey, 2012; Bailey, 2009) 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 techniques, besides pesticide. The techniques can be functionally grouped as in 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”, according to their function. Each portfolio is treated as a type of production technology in the rest of the paper (see Battisti and Iona (2009) for a similar approach for management practices). The groupings are shown in table 3.1.

Table 3.1

Alternative pest control techniques and their portfolio groupings (*with abbreviations in brackets*)

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

Table 3.2

Commitment to use of alternative pest control techniques

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 3.2. 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 3.3 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 3.3

Distribution of farmers by the number of techniques 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, initial adoption is calculated by a variable that takes the value of 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 3.4. The chemical user and weed focussed portfolios are most widely adopted with adoption rates of 95 percent and 93 percent of the sample 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 initial adoption of the portfolios.

Table 3.4

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 intensification 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). Our model considers the use of information at the time of adoption, so that the theoretical predictions do not distinguish between technology currently used and formerly used.

We summarise the extent of use in table 3.5. Distributional statistics are shown for each portfolio, with percentages showing the statistics divided by the number of technologies in the portfolio. Mean intensification rates are lower than initial adoption 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 3.5

Descriptive statistics for intensification of pest control portfolios based on sums of adoptions of component technologies

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

The percentages show the total number of component technologies adopted in each portfolio, divided by the total number of technologies in the portfolio.

As an alternative measure of intensification, 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 3.6. For each source, farmers respond either never (coded as one), rarely (coded as two), occasionally (three), or frequently (four).

Table 3.6

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)
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”. We consider the effect of alternative grading approaches in the results section.

Table 3.7 summarises the use for each information source. There is considerable variation in the rates of use across sources. The source with the lowest rates of use is academics (26 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 3.7

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%
FWeekly	181	341	522	65%
FGuard	331	191	522	37%

We also take various questions from the data to construct ancillary determinants for our equations. These are both discrete and continuous variables. In order to ensure parameter identification, we employ distinct determinants for technology adoption and information use, as well as shared ones. As is common in the literature, determinant selection is guided by data availability, theoretical plausibility, and prior work indicating their relevance. The variables are shown in table 3.8. As the arguments for inclusion of the variables are presented at length, we describe the rationale for selection of the variables in Appendix B.

Table 3.8

Non-information determinants

Technique adoption	Information use
Years of farming	Years of farming
Formal education	Formal education
Total agricultural area	Total agricultural area
Full time farming indicator	Full time farming indicator
Environmental scheme use	Internet access score
Environmental group consultation	

A final determinant ("local adoption") is the extent of adoption by other farmers in the same postcode district, which aims to measure how much can be learnt about the technology from other adopters in the area. This is often taken to reflect the existence of an "epidemic" effect of technology adoption due to external influence, and can also capture the effect of stock and order effects (Karshenas and Stoneman, 1993) where later adopters gain less from the adoption than early adopters. These offsetting effects can make the impact of the number of past adopters on the current adoption rates ambiguous (see for example Battisti et al (2007)). In estimations where the dependent variable is a binary variable measuring initial adoption for a farm, we define the local extent of adoption as the sum of similar binary variables for neighbouring farms, and excluding the original farm. In estimations where the dependent variable is count data measuring adoption intensity, we define the local extent of adoption as the sum of similar count data variables for neighbouring farms.

The availability of external information on the technology is distinct from the actual use of it, as measured by farmers' reports in our main determinant variables, because the latter also reflects access, quality, preferences, and other factors. Nevertheless, there is a likelihood of collinearity between local adoption and use of farmers as an information source. When local adoption is excluded as a determinant variable from the estimations in a working paper version of this paper, our conclusions do not change (see Waters (2013)).

3.4 Classification of information sources

In this section we classify the information sources used by the farmers in our data. The classification is whether the sources provide exploratory information which reduces uncertainty about a technology's performance, or whether they provide technical information which increases the income from use of the technology. We can then use the theory to predict how each type of information will affect either initial adoption or intensification of use of a technology.

Independent crop consultants (ICC)

Crop consultants provide information to farmers on all facets of crop management. The information may cover environmental and organic issues, as well as fertility, soil sampling, nutrients, growth and development, insects, weeds, disease, manure, hybrids, varieties, equipment, and hiring (Iowa Independent Crop Consultants Association, 2013). They usually operate commercially, with charges levied in proportion to the size of land about which they issue advice (Association of Independent Crop Consultants, 2013). Their focus on crop matters, and sensitivity to farmer requirements as a matter of financial survival, makes it likely that they would be able to issue recommendations that can be accurate evaluations of technology performance and also able to improve its use. Independent crop consultants are not linked to suppliers of recommended products, so claim to be unbiased (Association of Independent Crop Consultants, 2013). If farmers then perceive them to be reliable because of their independence, their information may be used without extensive examination so strengthening them as sources of exploratory information. As agronomists, they are professionally connected with academic agronomy and its research, even if they are not active researchers themselves. They may be able to use academic research to recommend and support implementation of complicated techniques, so strengthening their provision of technical information.

Empirically, a number of papers have examined the effect of farm advisors on initial adoption, particularly the impact of extension agents. Koundouri et al (2006) find that more extension visits to a farm is associated with higher probability of adopting an irrigation technology. In Abdulai and Huffman (2005), contact with extension agents accelerates initial adoption of crossbred cows. The acceleration is significant during the later phase of inter-firm diffusion. Genius et al (2006) similarly find that contact with extension agents increases adoption of organic technology, with the same finding in Läpple and Van Rensberg (2011). A slight qualification is in Tiffin and Balcombe (2011) who find that reliance on an agricultural advisory service as the main info source reduces initial adoption of organic production relative to reliance on other farmers. Genius et al (2006) look at how extension agents influence intensification, as well as initial adoption. They find that extension has a marginally larger positive effect on intensification than on initial adoption.

In summary, our theory suggests that independent crop consultants will provide both exploratory and technical information, and will be influential in both initial adoption and intensification of organic techniques. Empirically, some published evidence suggests that consultants will influence initial adoption, and there is limited evidence that they will also affect intensification. We therefore expect that they will alter both initial adoption and intensification in our data.

Land agents or similar professional persons

Land agents provide support in the sale or development of property. They operate commercially and so in order to survive they have to respond to farmer concerns. Some are large, experienced, and have research departments to monitor emerging market opportunities (Knight Frank, 2013). On the other hand, if advising on technology adoption occurs at all, it is only incidental to their main service. Thus, while land agents may provide some exploratory information on technology, we do not expect them to provide technical information.

Academic researchers

UK academics research all aspects of farming, including technology innovation and adoption. Organic farming is studied by individual specialists or at centres (for example at the Organic Centre Wales, based at Aberystwyth University). Universities often seek links with the private sector, for example through visits by one party to the other, collaboration, teaching, training, and student visits and sponsorship. The provision is likely to be stronger to farms located near larger research centres. Given the nature of universities' core work, we expect their information to be mostly on the technical side rather than exploratory.

Suppliers

Suppliers sell goods and equipment to farmers, and their revenue depends on the valuation that the farmers place on the sold items. The valuation of a technology will rise for risk-averse farmers if there is less uncertainty about its performance. Uncertainty may be reduced by providing the farmer with exploratory information about the technology, so a supplier may find doing so increases their income. However, suppliers have an interest in presenting technologies favourably to facilitate a sale, so their information may be biased. Supplier information on technology can also be technical (see for example Agricultural Supply Services (2013)), and they may engage in outreach through telephone or electronic contact, agricultural fairs, or visits to farms. They are motivated by profit to provide sufficient information to farmers to attract them to technology. In summary we expect suppliers to provide both exploratory and technical information, with some caution about their role in providing the former.

Buyers

Buyers may be consumers of a farm's output, in which case they benefit from lower output costs or higher valuation of the good. Alternatively, they may be intermediaries between a farm and the consumer or further intermediaries, and their interests are in lower output costs and higher valuation at the next stage of production. These interests may be met by efficient production, risk sharing, and fluid information.

The outcome can be tight coordination between buyers and farmers, with highly prescriptive production processes that preclude environmentally friendly practices. Such arrangements are dominant in the poultry industry, with frequent use in other parts of farming too (Hinrichs and Welsh, 2003). On the other hand, buyers may sometimes enforce sustainable or organic practices on a wide scale if they reflect consumer concern. Thus, supermarkets have issued to their suppliers restrictions on insecticides (Farmers Weekly, 2013a), requirements for certification by non-profit conservation groups (Farmers Weekly, 2013b), and requirements on animal feed to be non-genetically modified or explicitly permit it (Tesco, 2013). Such technical prescriptions are likely to apply for all goods meeting certain criteria, and have to be followed to make sales and profits from the buyers. Buyers can therefore provide exploratory information to farmers about current technologies, and technical information on how to implement them.

The empirical econometric evidence on the effect on farm technology adoption of using buyer information appears limited. Tiffin and Balcombe (2011) look at the impact of using buyers as the main source of information on initial adoption of organic production, and find that adoption is lower. However, their result is comparative, with the adoption rates calculated relative to those that occur when other main sources are used instead, so using buyer information does not correspond to a reduced absolute rate of organic adoption.

Other farmers

There are many reasons why farmers may provide information relevant to the adoption process. Local farmers may provide a visible demonstration of a technology in practice, and may interact on an extended, two-way basis. They may offer diversity of experience that cannot be matched in other media sources, particularly in less conventional productive techniques such as organic farming. On the other hand, they may be unwilling to share sensitive technical information, and their knowledge may be narrowly relevant to their own farm.

Empirical evidence supports the claim of a positive learning effect from other farmers, in initial adoption and, to a lesser extent, intensification. Bandiera and Rasul (2006) examine initial adoption of sunflower production by Mozambican farmers. They find that adoption by others in a farmer's social network changes initial adoption, but in a non-linear way. In Young (2009), learning from others' experience helps to explain initial adoption of hybrid corn using data from Ryan and Gross's (1943) early study. Tiffin and Balcombe (2011) discover that having other farmers as a farmer's main information source increases initial adoption. Conley and Udry (2010) look at intensification of fertiliser usage following a farmer's transition to pineapple production in Ghana. They find that it can be partially explained by the experience of people with whom a farmer shares information. Foster and Rosenzweig (1995) determine that the average experience of people in a village positively influences intensification by farmers, but not significantly.

On balance of the theoretical arguments and empirical evidence, we consider that farmers will primarily provide exploratory information.

DEFRA

The Department for Environment, Food & Rural Affairs is a government department and so has financial resources far exceeding most other information providers. The resources are manifest in the variety of means of contacting it, which include workshops, clinics, newsletters, text messages, and a helpline. Exceptionally among information providers, it also acts as a source of funding and regulation, and it gives much detail on these matters. Its dedicated Farming Advice Service (DEFRA, 2013) provides information on several topics relevant to organic farming. It describes conditions for environmental management that farms must meet in order to obtain government funding, including for organic schemes. It gives guidance on nutrients and fertilisers, and on climate change adaptation and mitigation. Given DEFRA's remit, resources, and current information provision, we anticipate that its information will be both exploratory and technical. Our model then implies that the information will be used in both initial adoption and subsequent intensification.

Newspapers

The Farmers Weekly magazine and Farmers Guardian weekly newspaper provide news reports on all aspects of farming. There are many articles on organic farming (a search of the Farmers Weekly website for articles containing "organic farming" produced 292 results in early 2014). These articles discuss the subsector's prospects, regulation, and consequences, as well as on techniques (for example, Farmers Weekly (2010)). As generalist publications aimed at a wide farming audience, their articles are likely to highlight the major trends in organic farming but may not have the same depth as information from a consultant or government. Moreover, their interaction with their individual readers tends to operate in one direction only, and they cannot interact heavily with individual farmers because of resource limitations.

Läpple and Van Rensberg (2011) examine empirically the effect of media information on initial adoption of organic farming in Ireland. They find that media are highly significant determinants of increased adoption. Tiffin and Balcombe (2011) examine initial organic adoption by UK farmers. They discover that farmers who rely on the press as their main information source tend to adopt less frequently than those who rely on other farmers. Considering both our theory and these prior empirical analyses, we expect the Farmers Weekly and Farmers Guardian to give exploratory but not technical information. They would then influence initial adoption but not intensification.

We summarise our expected results across all sources in table 3.9. The expectations will be compared with actual source effects observed in our data.

Table 3.9

Sources of information, type of information provided (exploratory / technical), and the expected adoption that they influence (initial / intensification)

Source	Type	Expected
ICC	Both	Both
Agents	Exploratory	Initial
Academe	Technical	Intens
Supplier	Both	Both
Buyers	Both	Both
Farmers	Exploratory	Initial
DEFRA	Both	Both
FWeekly	Exploratory	Initial
FGuard	Exploratory	Initial

3.5 Estimation procedure

In this section we describe our estimation procedure. Our theory proposes which sources of information will be associated with initial adoption and intensification. 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, p.823) 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 univariate adoption models containing all information variables as determinants and neglecting their endogeneity (as in Wozniak (1987)). This approach makes allowance for the simultaneous effect of the information variables. For initial adoption a probit model is used, while for intensification a Poisson model is used. The other approach is to treat the individual information sources as endogenous in systems with technology adoption as the other determined variable. As identification of coefficients in multiple information equations is not possible with our available data, we consider successive bivariate systems of technology adoption and individual technology source use. For the initial adoption model, a bivariate probit is used with information endogenous in the technology adoption equation. For intensification, a probit-Poisson model is used with technology as a treatment effect and a Heckman correction.

Parameter estimation

Initial adoption, exogenous information

We first consider the initial adoption of organic farming when information source use is exogenous. Influences on initial adoption are estimated through the following equations describing a farmer's technology adoption

$$z_1 = x_1'\beta_1 + i'\gamma + \varepsilon_1 \tag{3.12}$$

$$t = 1 \quad \text{if } z_1 > 0 \text{ and 0 otherwise,} \tag{3.13}$$

where z_1 is a latent variable measuring the combined effect of deterministic and stochastic adoption influences on adoption, 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 initial adoption for one of the technology portfolios. The model then has the probit form for initial adoption, and we estimate it across our UK farmer data for adoption within each technique portfolio. All information sources are included as simultaneous determinants.

Initial adoption, endogenous information

We then consider initial adoption when the information source use variables in equation (3.12) are endogenous. For identification purposes, the dimensions of the information vector i and its coefficient vector γ are set equal to unity. For each information source i, we introduce a pair of equations to describe the farmer's use decision

$$z_2 = x_2'\beta_2 + \varepsilon_2 \tag{3.14}$$

$$i = 1 \quad \text{if } z_2 > 0 \text{ and 0 otherwise} \tag{3.15}$$

where z_2 is a latent variable measuring the combined effect of deterministic and stochastic adoption influences on adoption, x_2 is a vector of determinants of use that may overlap with the technology adoption determinants 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 $\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$.

The equations (3.12)-(3.15) are solved as a recursive bivariate probit system for technology adoption within each portfolio and each information source. Estimation is by maximum likelihood. The *i* information variable is correlated with the error variable ε_2, so will generally be correlated with ε_1 via the correlation of ε_1 and ε_2. However, the endogeneity can be neglected in solving the log likelihood (Greene, p823). The probability $P(i=1, t=1)$ can be written as $P(i=1)P(t=1 \mid i=1)$, which controls for the endogeneity. Because of the properties of conditional probability, the term $P(t=1 \mid i=1)$ can be written as $\Phi_2(x_1'\beta_1 + i'\gamma, x_2'\beta_2, \rho)/\Phi(x_2'\beta_2)$. Here $\Phi_2(z_1, z_2, \rho)$ is the bivariate normal cumulative distribution function to points z_1 in the first standard normal variate and z_2 in the second standard normal variate with covariance of ρ between the two variates, and $\Phi(z_2)$ is the cumulative distribution function to point z_2 for a standard normal variate. The term $P(i=1)$ equals $\Phi(x_2'\beta_2)$, so $P(i=1, t=1) = \Phi_2(x_1'\beta_1 + i'\gamma, x_2'\beta_2, \rho)$, which is the same as the bivariate probability treating the *i* variable as exogenous. The same approach can be used for the other probabilities in the log likelihood, $P(i=1, t=0)$, $P(i=0, t=1)$, and $P(i=0, t=0)$, showing that they also can be calculated as if the *i* variable was exogenous.

Intensification of adoption, exogenous information

We next turn to intensification of organic farming adoption when information sources are exogenous. The effects of information sources on intensification are examined using a Poisson model for technology adoption. The probability of a farmer adopting *T* techniques is given by

$$P(T) = \frac{e^{-\lambda}\lambda^{T}}{T!}$$

where

$$\lambda = \exp(x_1'\beta_1 + i'\gamma)\,.$$

x_1, i, β_1, and γ are the same as for equations (3.12) and (3.13). Estimates are produced for each portfolio separately, with the number of techniques used in them as the determinant. All information sources are included as simultaneous determinants.

Intensification of adoption, endogenous information

Our final specification examines intensification of organic farming when information sources are endogenous. For each information source *i*, the information use equations are given by equations (3.14) and (3.15) again. Given the use of information source *i*, the probability of the farmer adopting *T* techniques in a portfolio is

$$P(T \mid i, \varepsilon_1) = \frac{e^{-\lambda}\lambda^T}{T!}$$

where

$$\lambda = \exp(x_1'\beta_1 + i'\gamma + \varepsilon_1)\,.$$

ε_1 and ε_2 are bivariate normal with zero means and a covariance matrix $\begin{pmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}$.

Solution is by maximum likelihood estimation for each pair of information source use and portfolio technique adoption. Terza (1998) formulates the full information maximum likelihood for a class of endogenous switching models including the one presented here, and we follow their scheme. From the conditional properties of the bivariate normal distribution, and equations (3.14) and (3.15), the distribution of i conditional on ε_1 is given by

$$P(i \mid \varepsilon_1) = i\Phi\left(\frac{x_2'\beta_2 + (\rho/\sigma)\varepsilon_1}{\sqrt{1-\rho^2}}\right) + (1-i)(1-\Phi\left(\frac{x_2'\beta_2 + (\rho/\sigma)\varepsilon_1}{\sqrt{1-\rho^2}}\right)).$$

It follows that the joint distribution of i and T is given by

$$f(i,T) = \int_{-\infty}^{\infty} P(T \mid i,\varepsilon_1) P(i \mid \varepsilon_1) f(\varepsilon_1) d\varepsilon_1$$

or

$$f(i,T) = \int_{-\infty}^{\infty} P(T \mid i,\varepsilon_1) P(i \mid \varepsilon_1) \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{\varepsilon_1^{\;2}}{2\sigma^2}) d\varepsilon_1$$

After formation of the log likelihood function, the maximum is found through Gauss-Hermite quadrature.

Non-information determinants

The set x_1 of non-information determinants of technology adoption is taken to be the variables on the left hand side of table 3.8 together with the level of local adoption, while the set of determinants of general information usage is taken to be the variables on the right hand side of the table.

Our STATA code is available from the author. The data used cannot be provided as its dissemination is restricted; nevertheless it is freely available to researchers at the UK Data Service website[1].

3.6 Empirical results

In this section we present our empirical results. They are given in turn for the intra-crop bio-controller portfolio, the chemical users / conserver

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

portfolio, the extra-crop conservation bio-controller portfolio, and the weed focussed farmer portfolio. We discuss in detail the results for the intracrop portfolio to examine the consistency of the empirical results with our theoretical model in an individual case. We then produce condensed statistics for all the portfolios together to show aggregate agreement with our model.

Table 3.10 shows the estimates of initial adoption for the intracrop portfolio, and part one of the table has the coefficients for the information variables. The first column presents estimates for a single probit equation including all information variables simultaneously. Collinearity between information and the other determinants is neglected, so the coefficients on the information variables may absorb some of the effect of the other variables. Land agents have a weakly significant effect on initial adoption, in line with our theoretical expectation. The same is true for farmers. Buyers have a moderately significant effect on adoption, as expected. No other variables are significant.

The remaining columns in the top panel of table 3.10 report estimates for recursive bivariate probit models with one source of information jointly determined with adoption. The adoption equation in this bivariate system gives an information coefficient that measures the direct deterministic effect of information. All information source coefficients are highly significant. In a recursive bivariate model with high cross-equation error correlation, the direct effects are not in themselves very informative because they do not allow for how information use affects the error in its determining equation, and hence how it changes the correlated error in the adoption equation. The effect of information may act through omitted terms affecting adoption through the error term. We address the full marginal effects including stochastic effects shortly.

Table 3.10, part two shows estimates of the effect of other determinants on initial adoption in the intracrop portfolio. Years of farming tend to have a negative effect on initial adoption but the coefficients are not significant;

we had no prior expectations on the effect. Formal education is broadly associated with reduced initial adoption without much significance; we anticipated increased adoption. Farmers with larger farms adopt significantly more often. We had no prior expectations of size's effect. We also had no expectations of the effect of being a full time farmer, and we find that they tend to adopt more frequently but without statistical significance. Users of environmental schemes have increased initial adoption as we expected, without statistical significance. Consultancy of environmental groups significantly increases adoption rates in line with expectations. Adoption in the locality is associated with increased adoption; we did not have a prior expectation on its effect. The correlations between the technology initial adoption and information use equations are both positive and negative, and generally high in absolute value. It follows that stochastic influence of information on initial adoption is often important. However, for several information sources the correlation coefficients are highly insignificant.

Table 3.11 shows estimated coefficients on the determinants of information use for the intracrop portfolio's initial adoption. Years of farming are generally associated with lower adoption, sometimes significantly. We had no anticipated sign of effect. Formal education significantly increases the use of information from independent crop consultants, land agents, and academics. Their information may be expected to be quite technical, so that education may lead to either increased understanding of, or respect for, it. Education reduces reliance on information from the Farmers Guardian newspaper with marginal significance. Our prior expectation was that education would increase information use, particularly from technical sources, so there is some support for our expectation from these findings. Larger farms are often associated with increased information use, with significance in the case of information from land agents, academics, and the Farmers Weekly magazine. Our prior expectation was that consultants, agents, suppliers, and buyers would be favoured as sources on larger farms. Full time farmers generally have increased use of information sources, with marginal significance in the case of independent crop consultants and high significance in the case of the Farmers Weekly magazine and Farmers Guardian newspaper. We had no prior anticipation on effect signs. The quality of internet access (where a lower score is associated with better access) has a mixed impact on information use, with significantly decreased use of information from suppliers and the Farmers Guardian and significantly increased use of buyer and Farmers Weekly information. The reasons for these results are not immediately clear, and are contrary to our anticipated increase in information use due to internet access. Perhaps some information sources are easier to use than others when the internet is more available.

The marginal effects of information determinants on initial adoption of the intracrop portfolio are shown in table 3.12. The first column has the marginal effects for the probit model treating information as exogenous. As the model is univariate, the significant information sources and their signs are the same as for the coefficient estimates: agents and buyers have a significant positive marginal effect and farmers have a negative marginal effect.

The other columns in table 3.12 present the marginal effects of the sources allowing for the direct effect and stochastic effect acting through the correlated error terms. Independent crop consultants have a moderately significant positive effect and land agents have a highly significant positive effect on initial adoption. These two findings are consistent with expectations. Academic sources have no significant impact, as expected. Suppliers do not affect initial adoption significantly, contrary to our expectations, but buyers do, which we anticipated. Farmers do not affect adoption, contrary to anticipation. As we expected, information from DEFRA has a significant influence on adoption. Both the Farmers Weekly and Farmers Guardian positively influence adoption, with the latter highly significant and the former narrowly missing significance. These findings are consistent with our theoretical expectations.

We now turn to intensification of use in the intracrop portfolio. Table 3.13, part one shows the coefficient estimates for information sources' effects on intensification. The first column presents the estimates of a Poisson model where information sources are treated as exogenous and included simultaneously. Information from independent crop consultants has a positive, significant effect on intensification, consistent with our expectations. Land agent information misses having a significant effect, as anticipated. Academic information has no significant effect, contrary to expectations. Supplier information is entirely insignificant in its effect on intensification, also contrary to our expectations. Intensification is significantly increased by buyer information as we expected, while farmer information misses a significant impact, in line with our anticipated finding. Information from DEFRA is associated with a significant increase in intensification, as expected. Neither the magazine nor the newspaper affect intensification. No effect was anticipated.

The other columns in table 3.13, part one report estimates from bivariate Poisson treatment models with use of individual information sources determined endogenously. The coefficients show the direct effect of information on intensification, with only suppliers, farmers, and the Farmers Guardian newspaper having no significant direct impact. While the findings of farmers and the newspaper having no deterministic effect are consistent with our theoretical model (but not the finding on suppliers), in the bivariate model the effect of information sources acts both through its deterministic and stochastic effects, and we consider their combined marginal effect presently.

In table 3.13, part two we see how the non-information determinants affect intensification. Farming experience is associated with reduced intensification, but not generally significantly so. We did not anticipate any relation. Formal education is associated with reduced intensification; we had no expectations on the relation. A possible explanation is that education may be a relatively complementary asset to conventional farming, whereas it may be less of an advantage in organic farming with lower scientific and technological complexity in inputs. The size of the farm is associated with some increase in intensification, but does not have a broad significant effect. We anticipated a negative effect, and do not have any reason immediately available to explain the difference. Being a full time farmer is associated with more intensified use of intracrop techniques, and often significantly. We did not have any prior expectations on the existence of an association. Environmental scheme use is associated with greater intensification and with high significance, consistent with our expectation. The same applies for consultation of environmental groups. Local adoption increases intensification; we did not anticipate a relation one way or the other. The cross-equation correlations between the intensification equation and information use equations are generally high in absolute value, although they are not always significant. Thus, information often influences adoption through a stochastic as well as a deterministic route.

In table 3.14 we can see the estimated coefficients on determinants of information use for intracrop intensification. More experienced farmers tend to use all forms of information less frequently. We had no prior expectation on the sign of an effect. Formal education significantly increases the use of independent crop consultant information, and significantly reduces use of the Farmers Guardian newspaper. The other information sources are generally affected positively but without significance. The results are as expected. Larger farms are associated with significantly more use of consultant information as anticipated, but contrary to expectations size doesn’t significantly change use of information from land agents, suppliers, or buyers. It does increase use of the Farmers Weekly magazine. Farming full time is associated with increased use of most information sources, but only significantly so in the case of independent crop consultants (weakly) and the two press sources (strongly). We had no prior expectation on the effect of full time farming. Improved internet access (where a lower score is associated with better access) has mixed effects on use of information sources, with some sources being used more and some less. The only two significant effects are on the

Farmers Weekly magazine, where use increases, and on the Farmers Guardian newspaper, when use falls. We expected that internet use would increase information use, and the gap with the actual results may perhaps be explained by internet use complementing some sources and rendering others superfluous.

Table 3.15 shows the marginal effects of use of each information source. The first column reports marginal effects for the Poisson model. The effects have the same sign and significance as for the coefficient estimates, with independent crop consultants, buyers, and DEFRA providing significant information. It was anticipated that all three would influence intensification. Farmers also provide marginally significant information, contrary to expectations. The remaining columns report the marginal effects for the Poisson treatment model, where the effect of information sources on intensification acts through deterministic and stochastic routes. Independent crop consultants have a highly significant positive effect on intensification, consistent with expectations. Land agents are also very significantly associated with intensified usage. We thought that there would be no effect. Academic information is associated with very significantly less intensification, as expected. Supplier information has no significant effect on intensification, contrary to our expectations. Information from buyers significantly increases intensification, also in line with expectations. Farmer information has no significant effect on intensification. We considered that farmer information would not influence intensification. Information from DEFRA has a highly significant positive effect on intensive usage, as expected. Information from the two press sources has a weak effect (Farmers Weekly) and no significant effect (Farmers Guardian), and none was anticipated.

Table 3.10, part one

Estimated coefficients for information determinants of initial adoption of an intracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.2129	1.4384***								
	0.1433	0.492								
Agents	0.2216*		-1.0650***							
	0.1215		0.3268							
Academia	-0.0516			-1.4736***						
	0.1347			0.079						
Suppliers	0.2159				-1.5249***					
	0.1521				0.0782					
Buyers	0.2673**					1.6234***				
	0.125					0.0758				
Farmers	-0.2417*						-1.4500***			
	0.1307						0.1895			
DEFRA	0.0851							1.2813***		
	0.1256							0.4386		
Farmers Weekly	0.0342								1.4695***	
	0.1278								0.1396	
Farmers Guardian	0.0826									-0.9729***
	0.1239									0.3709

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.10, part two

Estimated coefficients for non-information determinants of initial adoption of an intracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0019	-0.001	-0.0055	-0.0042	-0.006	0.0025	-0.0105**	-0.0014	0.0045	-0.0057
	0.0052	0.0049	0.0047	0.0045	0.0045	0.0045	0.0047	0.0048	0.0047	0.0049
Formal education	-0.0612	-0.1100*	0.0394	0.0929*	-0.0499	-0.0764	-0.0184	-0.0664	-0.0678	-0.0876
	0.0624	0.0601	0.0685	0.0535	0.0531	0.0529	0.0551	0.0561	0.0537	0.0581
Hectares	0.0005***	0.0004*	0.0006***	0.0006***	0.0004***	0.0004***	0.0004**	0.0005**	0.0002	0.0005**
	0.0002	0.0002	0.0002	0.0002	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002
Full time	0.2208	0.0939	0.1311	0.1946	0.207	0.0751	0.2377*	0.1365	-0.0743	0.3576**
	0.1557	0.1669	0.1533	0.1354	0.1321	0.133	0.1372	0.1589	0.1462	0.1486
Environ schemes	0.104	0.0953	0.0537	0.0186	0.0809	0.0816	0.0424	0.0743	0.0938	0.0856
	0.1144	0.0974	0.0815	0.0708	0.0764	0.0754	0.0829	0.0912	0.0783	0.0926
Environ consults	0.2957*	0.3315**	0.2603*	0.3534***	0.2379***	0.2079**	0.3216***	0.3229**	0.2613**	0.3494**
	0.1535	0.1415	0.1356	0.0896	0.0715	0.0937	0.1195	0.1466	0.1149	0.1361
Local adoption	0.0194**	0.0203**	0.0159*	0.0132*	0.0140*	0.0037	0.0211***	0.012	0.0151*	0.0330***
	0.009	0.0085	0.0088	0.0076	0.0077	0.0076	0.008	0.0101	0.008	0.009
Constant	-1.0926**	-1.4437***	-0.1408	-0.518	0.9568**	-0.8983**	0.7048	-1.2340***	-1.3629***	-0.1983
	0.5108	0.4448	0.4389	0.3695	0.3891	0.3744	0.4765	0.4186	0.386	0.4748
ρ		-0.7251	0.842	1	1	-0.9998	0.8941	-0.7303	-0.9135	0.7087
p-value		0.2402	0.1218	0.9902	0.9778	0.9103	0.0767	0.1904	0.0484	0.0637
(Pseudo) R^2	0.0772									

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. The p-value is for a test of ρ=0. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.11

Estimated coefficients for determinants of information use for initial adoption of an intracrop technology

	Icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0028	-0.0077	-0.0067	-0.0097**	-0.0063	-0.0155***	-0.0014	-0.0103**	-0.0088*
	0.0054	0.005	0.0052	0.0049	0.005	0.005	0.0051	0.0051	0.0052
Formal education	0.1587**	0.1540**	0.2502***	-0.0301	0.0884	0.0334	0.0574	0.0463	-0.1085*
	0.0623	0.0602	0.0619	0.0607	0.0598	0.0592	0.0589	0.0593	0.0613
Hectares	0.0003	0.0003*	0.0003*	-0.0001	0.0001	0.0000	0.0001	0.0008***	0.0000
	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0003	0.0001
Full time	0.2811*	-0.0973	0.0982	-0.0531	0.1726	0.1466	0.1168	0.3883***	0.4488***
	0.1585	0.1484	0.1649	0.1384	0.1483	0.1495	0.1485	0.1463	0.1639
Internet score	0.0001	0.0483	0.0418	0.0640***	-0.1298***	0.0653	-0.0664	-0.0984**	0.1524***
	0.0595	0.0435	0.0345	0.0227	0.0422	0.0407	0.0492	0.0416	0.0507
Local adoption	-0.0055	0.0028	-0.0029	0.0008	0.0161*	0.0113	0.0109	0.0035	0.0386***
	0.0091	0.0086	0.0086	0.0087	0.0082	0.009	0.0088	0.0088	0.0087
Constant	0.0083	-0.5784	-1.6428***	1.1797***	-0.3947	0.5133	0.208	0.3621	-0.7147*
	0.4153	0.3889	0.3846	0.3884	0.3798	0.3903	0.3923	0.3808	0.4043

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by recursive bivariate probit with the initial adoption of the technology jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.12
Marginal effects of using an information sources on initial adoption of an intracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	Fguard
ICC	0.0776	0.1168**								
	0.0519	0.0538								
Agents	0.0807*		0.1073***							
	0.0439		0.0151							
Academia	-0.0188			-0.0198						
	0.0491			0.0139						
Suppliers	0.0787				0.0455					
	0.0551				0.0723					
Buyers	0.0974**					0.1358***				
	0.0449					0.0157				
Farmers	-0.0881*						-0.0437			
	0.0472						0.0407			
DEFRA	0.031							0.0706**		
	0.0457							0.0321		
Farmers Weekly	0.0124								0.0662	
	0.0465								0.0411	
Farmers Guardian	0.0301									0.0674***
	0.0451									0.0113

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.13, part one

Estimated coefficients for information determinants of intensification of an intracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.3268**	2.2753***								
	0.1365	0.3051								
Agents	0.1438		2.3882***							
	0.1027		0.2588							
Academia	-0.1765			-2.1578***						
	0.1151			0.234						
Suppliers	0.0299				-0.3284					
	0.1256				0.7216					
Buyers	0.2329**					2.2242***				
	0.1023					0.2464				
Farmers	-0.1818*						-0.7188			
	0.1069						1.0253			
DEFRA	0.2426**							2.2947***		
	0.1118							0.2475		
Farmers Weekly	-0.0217								1.4082**	
	0.1087								0.571	
Farmers Guardian	0.0676									-0.6481
	0.1031									0.5206

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.13, part two

Estimated coefficients for non-information determinants of intensification of an intracrop technology

	All	icc	agents	academe	supplier	buyers	Farmers	defra	fweekly	fguard
Years farming	-0.006	-0.0036	0.003	-0.0119**	-0.0073	-0.0029	-0.0103	-0.0052	0.0001	-0.0087
	0.0045	0.007	0.0055	0.0052	0.0057	0.0058	0.0076	0.0062	0.0067	0.006
Formal education	-0.1211**	-0.2450***	-0.2158***	0.0826	-0.1164*	-0.1341*	-0.1057	-0.1437*	-0.1459**	-0.1406*
	0.0532	0.0769	0.0662	0.0705	0.0663	0.0697	0.0672	0.077	0.0731	0.0725
Hectares	0.0001	0.0000	0.0000	0.0002**	0.0001	0.0001	0.0001	0.0001	0.0000	0.0001
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Full time	0.1996	0.0428	0.3598**	0.5125***	0.2621	0.0638	0.2821	0.1888	0.0387	0.3675*
	0.1419	0.2007	0.1685	0.1783	0.1742	0.1799	0.1781	0.2098	0.211	0.2
Environ schemes	0.2971***	0.3367***	0.2579**	0.2927**	0.2993**	0.2740**	0.2885**	0.2950**	0.3140**	0.3094**
	0.1057	0.127	0.1275	0.1286	0.1286	0.1281	0.1284	0.127	0.1285	0.1287
Environ consults	0.3431***	0.4367***	0.3696**	0.4934***	0.5409***	0.4071***	0.5464***	0.3964***	0.4864***	0.5186***
	0.129	0.1521	0.154	0.1499	0.1551	0.1555	0.1556	0.1536	0.1556	0.1556
Local adoption	0.0069*	0.0118**	0.0093*	0.004	0.0092*	0.0004	0.0104**	0.0026	0.0088	0.0140**
	0.0038	0.0058	0.0048	0.0049	0.0049	0.0051	0.0053	0.0056	0.0054	0.0065
Constant	-1.2140***	-2.5142***	-2.2024***	-1.4618***	-0.9234	-1.6729***	-0.6395	-2.4824***	-2.0444***	-0.9793*
	0.4501	0.6298	0.5335	0.5303	0.8399	0.5311	0.9654	0.6329	0.6476	0.5749
ρ		-0.9764	-1	1	0.2896	-1	0.4624	-0.998	-0.8318	0.6069
p-value		0.0025	0.9444	0.9135	0.5729	0.9936	0.5494	0.7733	0.0648	0.1228

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. The p-value is for a test of ρ=0. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.14

Estimated coefficients for determinants of information use for intensification of adoption of an intracrop technology

	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.002	-0.0106	-0.0093	-0.0097*	0.0000	-0.0158***	-0.0003	-0.0099*	-0.0093*
	0.0054	0.3965	0.0156	0.0058	0.0063	0.0053	0.004	0.0051	0.0052
Formal education	0.1738***	0.1156	0.2411	-0.0395	0.0018	0.0288	0.0121	0.0481	-0.1146*
	0.0554	16.7868	0.4817	0.067	1.4546	0.0604	0.1456	0.0597	0.0612
Hectares	0.0003**	0.0004	0.0001	-0.0001	0.0000	0.0000	0.0001	0.0008***	-0.0001
	0.0001	0.0087	0.0004	0.0001	0.0141	0.0001	0.0016	0.0003	0.0001
Full time	0.2679*	-0.1718	0.2957	0.0491	0.0134	0.1141	0.0292	0.3869***	0.4282***
	0.15	0.9305	1.6085	0.1683	10.8347	0.1553	0.3531	0.1482	0.1635
Internet score	-0.0055	0.0071	0.0183	0.0667	-0.0012	0.0327	-0.013	-0.0972**	0.1556***
	0.0465	0.2436	0.7517	0.0616	0.9987	0.0595	0.1564	0.0483	0.0525
Local adoption	-0.0043	0.0018	-0.0071	-0.0008	0.0004	0.0052	0.002	0.0007	0.0188***
	0.0046	0.0527	0.0468	0.0052	0.3507	0.0049	0.0236	0.0048	0.0047
Constant	-0.0479	-0.1129	-1.5413	1.1474**	-0.3412	0.6735	0.2759	0.3408	-0.6429
	0.3662	93.3135	2.9232	0.455	19.2509	0.4329	0.5172	0.392	0.4076

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.15

Marginal effects of using an information sources on intensification of adoption of an intracrop technology

	All	Icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.2737**	1.8184***								
	0.115	0.4442								
Agents	0.1204		4.2838***							
	0.0862		1.1983							
Academia	-0.1478			-2.2498***						
	0.0967			0.4888						
Suppliers	0.025				-0.3123					
	0.1051				0.7747					
Buyers	0.1950**					4.3704***				
	0.0862					1.1939				
Farmers	-0.1523*						-0.7387			
	0.0898						1.334			
DEFRA	0.2031**							2.7155***		
	0.0941							0.6121		
Farmers Weekly	-0.0182								1.2603*	
	0.091								0.708	
Farmers Guardian	0.0566									-0.5574
	0.0864									0.4876

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

The effects of information on initial adoption and intensification in the intracrop portfolio are similar to our model's predictions, with some variation. We now introduce results for the other portfolios, which are reported in full in Appendix B. Rather than repeat the individual examination for each of these portfolios, we summarise our findings as a whole by constructing condensed statistics that measure how important each source is for initial adoption and intensification. In table 3.16, the entries for each portfolio-source cell are constructed by counting significance stars on the marginal effects in the corresponding entries in the initial adoption and intensification tables (tables 3.12 and 3.15, and the marginal effect tables in Appendix B), and summing the two numbers. Thus, each entry lies between zero and six inclusive. The two right hand columns sum across the portfolios to get measures of source importance for overall initial adoption and intensification. Table 3.17 expresses the overall observed effects in comparison to the expected effects.

Information from independent crop consultants has a strong influence on both initial adoption and intensification, as expected. It affects initial adoption more strongly. Land agent information affects both forms of adoption, with the impact on intensification weak. The results are in line with expectations. Academic information has a weak effect on initial adoption and intensification, with slightly greater influence on the latter as we expected. Information from suppliers has a similarly weak effect on both with slightly greater influence on intensification; we anticipated that it would influence both initial adoption and intensification. Buyer information affects both adoption types, in line with prior expectations. Farmer information affects mainly initial adoption, which we anticipated. Information from DEFRA affects both forms of adoption, as we anticipated, but has a stronger impact on intensification. The Farmers Weekly magazine has limited effect on intensification and the Farmers Guardian newspaper affects only initial adoption. Our expectation for these press sources was that they would only affect initial adoption. In summary, we obtain quite close agreement between our expectations and the observed outcomes.

Table 3.16

Sums of significance stars across marginal effects

	Intracrop		Chemical		Extracrop		Weed		Overall	
Source	Initial	Intens	Initial	Intens	Initial	Intens	Initial	Intens	Initial	Intens
ICC	2	5	5	3	4	2	4	0	15	10
Agents	4	3	0	0	2	0	0	0	6	3
Academe	0	3	0	2	2	0	1	0	3	5
Suppliers	0	0	4	5	0	0	0	0	4	5
Buyers	5	5	2	4	3	0	2	5	12	14
Farmers	1	1	0	0	2	0	3	0	6	1
DEFRA	2	5	0	1	4	0	0	5	6	11
FWeekly	0	1	0	2	0	0	0	0	0	3
FGuard	3	0	0	0	3	1	3	1	9	2

Table 3.17

Sources of information, the expected types of diffusion that they influence (initial / intensification), and the diffusion types they are empirically found to influence. (*A star indicates that the finding is not a strong result.*)

Source	Expected	Observed
ICC	Both	Both
Agents	Initial	Initial
Academe	Intens	Intens *
Supplier	Both	Both
Buyers	Both	Both
Farmers	Initial	Initial
DEFRA	Both	Intens
FWeekly	Initial	Intens *
FGuard	Initial	Initial

Results under alternative gradings of information use

The survey underlying our data asks farmers what information sources they use, with a response range of never, rarely, occasionally, or frequently. In the analysis so far, we have reduced these responses to a use measure taking the value zero if response is "never" or "rarely", and taking the value one if the response is "occasionally" or "frequently". In this subsection, we briefly examine results estimated under other definitions of the use measure. The first alternative definition is that an information source is considered to be used (and the use measure is set to one) only if it is used frequently. The second alternative measure is that a source is considered to be used if it is used rarely, occasionally, or frequently.

The summary results are presented in table 3.18, which shows whether a source is associated with initial adoption or intensification under the calculation method outlined before table 3.16. The third column of table 3.18 presents results when sources must be used frequently to be considered used at all. There are many differences between the expected and actual results. There is the possibility of misclassification introduced by our changed definition, which may account for some of the differences. Further, if use is necessarily frequent, it would tend to suggest a large amount of information is being extracted from the source. The use may then tend to be associated more with intensification. This mechanism might explain why using other farmers as a source is associated with increased intensification under frequent information use, but not when information is used less frequently. The fourth column of table 3.18 presents results when a source is deemed to be used no matter how light that use is. Most sources are found to influence both initial adoption and intensification. It is possible that some level of light information use tends to be associated with any adoption. If a farmer avoids any use of a particular information source, they may also be more avoidant of technology adoption than other farmers.

Table 3.18

Sources of information and the diffusion types they are empirically found to influence, under alternative definitions of information use

		Criteria on frequency of use if information use is considered to have occurred	
		Frequently	Rarely, occasionally, or frequently
Source	Expected	Observed	Observed
ICC	Both	Both / initial	Both
Agents	Initial	Both	Both
Academe	Intens	Initial	Both
Supplier	Both	Both	Both
Buyers	Both	Initial	Both
Farmers	Initial	Intens	Both
DEFRA	Both	Intens	Intens
FWeekly	Initial	Initial	Both
FGuard	Initial	Both	Initial

As another alternative grading of information use, we could retain the full four point scale. The estimation of the technology adoption equation when information is treated as exogenous would then seem to present no difficulties. However, if information is endogenous, the problems noted at the start of section 3.5 arise, namely parameter proliferation across the system equations and estimation difficulties. We do not attempt the four point grading here.

3.7 Conclusions

We have presented a model of the effect of information sources on initial adoption and intensification and tested it with UK farming data. Consistent with our model, we found evidence that initial adoption is often driven by exploratory information which provides an indication of the broad performance of a technology, while intensification is often driven by technical information which improves a technology's performance.

We find that information from farmers affects the extent of initial adoption, but not intensification. The result is consistent with the findings in Battisti and Stoneman (2005) for UK manufacturing, where the industry proportion of previous adopters of a technology does not significantly influence diffusion within companies. However, the result contrasts with Conley and Udry's (2010) finding that such information adjusts the intensification 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 farming information relevant to intensification, 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 intensification of new types of forage grasses, so conceivably the difference can be generalised to farmers in developing and developed countries.

We examined the role of farmers as an explicit information source, separating it from the other effects of the number of farmers in the surrounding region. The literature identifies various ways by which previous adopters may influence new adoption. The mechanisms include strategic interaction (Hoppe, 2000; Jensen, 2003; Mariotti, 1992; Reinganum, 1983), network externalities such as those existing in computer software (Brynfolfsson and Kemerer, 1996; Katz and Shapiro, 1985), and the presence of secondary markets (Cho and Koo, 2012). These mechanisms sometimes also describe relations between the presence of earlier adopters and information flows to a potential new adopter. Future work could examine whether the proposed flows are empirically supported. The mechanisms could also be adapted to allow for the relations between previous adoption rates and different types of information.

Our theoretical and empirical models could be modified to reflect other plausible determinants of information choice. The relative role of education in initial adoption and intensification could be assessed, and the comparative importance of economic and information determinants. The disclosure value associated with intensification could be examined, as could the extent to which information changes technology's effect on profitability.

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 initial adoption and intensification, although whether it is cost-effective is another issue. A further implication is that although UK farmers have some role in initial adoption, their role in intensification is not significant so network construction will not necessarily lead to much fuller diffusion.

Appendix 3.A

Rationale for inclusion of the non-information covariates in the technology adoption equation

Years of farming

Farming experience is measured by years spent farming. The general adoption literature describes potentially opposing effects of establishment age on adoption. Greater experience may allow for cheaper and more certain assessment of the value of a technology, so facilitating its adoption. Its use may also be easier. However, an older establishment may be more committed to an existing practice, or greater financial investment in it than a newer entrant. Older farmers or owners who are closely identified with their businesses may also have a shorter planning horizon and less willingness to invest. The empirical literature findings on establishment and entrepreneurial age has not indicated a clear dominance of one of the effects. Thus, Battisti et al (2004) find that older plants have reduced adoption rates of IT equipment and joint design teams, while in Battisti and Stoneman (2005) there is no significant relation between age and adoption. Bandiera and Rasul (2006) find older farmers are more likely to introduce a new crop, and in El-Osta and Morehart (1999) adoption of a capital intensive technology or a capital-management dual technology rises until farmers are in their 50s or 60s and declines thereafter. In Khanna (2001), experience does not influence the adoption of a relatively unsophisticated soil testing technology, but does influence the adoption of an associated, more advanced soil application technology. Läpple and Van Rensburg (2011) find that farmer age reduces adoption rates of organic farming, particularly among earlier adopters. Padel (2001) reviews the literature and finds that organic adopters are often younger and less experienced than adopters.

The results reported by Läpple and Van Rensburg (2011) and Padel (2001) may lead us to anticipate that experience will be negatively associated with adoption of organic farming generally. Organic farming, unlike many technological innovations, is associated with lower technological complexity than the practice it replaces. So experience does not lead to such a major advantage in assessing and managing its introduction as would be the case with more technologically advanced innovations, and we may expect the longer planning horizon of younger farmers to be more influential on adoption than the experience of older farmers. Whilst this may be true of organic farming as a combined practice, it does not necessarily follow for the advanced techniques of organic farming that we are analysing here. Conditional on adoption of organic farming, it may be the case that experience again becomes significant in the decision to adoption the techniques. Thus, we leave undecided the expected direction of influence of years of farming on technique adoption.

Experience may influence the utility and selection of information. A more experienced business person may find that their experiences act as a substitute for external information, and so have less demand for it generally. Alternatively, it may act as a complement to information, making information easier to assess and use. As with experience's effect on technology adoption, its effect on information use is two-edged. Perhaps reflecting the ambiguity, neither Ortmann et al (1993) nor Foltz et al (1996) find farmer age to be a statistically significant influence on use of consultants. It is perhaps more likely that experienced farmers would find relatively less value in general or non-technical sources of information and more value in detailed sources. However, in Gloy et al (2000), older farmers are to an extent more likely to find media sources (which are largely general sources in Gloy et al's classification) more useful than younger farmers, and younger farmers are to an extent more likely to find personal sources (which are largely technical) more useful. It is conceivable that experience remains a substitute for more technical information. This interpretation is perhaps contradicted by the results in Gervais et al (2001) that experienced Canadian farmers are more likely to use information from field days and workshops, academia, and newsletters and fact sheets. The employment of these relatively technical sources seems to indicate that experience complements these forms of information, although Gervais et al (2001) also find that confidence in these sources declines with experience. Given the uncertain effect of experience on information use, we form no prior expectation about it.

Formal education

Formal education is measured by a categorical variable taking the value of one if the respondent has some schooling, two if they have completed secondary school, three if they have some post secondary vocational training, four if they have a college diploma or certificate, and five if they have a university degree. As response to the variable is not our primary concern, for convenience we apply slightly more structure to the variable than is warranted by the data collection and treat it as continuous.

Companies with better educated workers may be expected to be able to evaluate the worth of a new technology, so plausibly would be more likely to adopt a technology initially. Education may be expected to ease implementation of a new technology and so increase its profitability, which would support both the initial adoption and subsequent intensification. Battisti et al (2009) in their analysis of European internet use find that education matters for initial adoption, but not subsequent intensification. Both Abdulai and Huffman (2005) and Bandiera and Rasul (2006) study Tanzanian farmers and determine that education is associated with increased technology adoption. The same is found in many developed country studies (El-Osta and Morehart, 1999; Foltz and Chang, 2002; Genius et al, 2006; Gillespie et al, 2009; Khanal et al, 2010; Khanal and Gillespie, 2011; Tiffin and Balcombe, 2011).

For organic farming adoption, the prior theoretical link between education and adoption is less clear than with other technologies. Whereas many new technologies embody increased scientific knowledge or greater capital content, organic farming represents an abandonment of some of the scientific techniques introduced in the last hundred years. Nonetheless, many papers have identified a connection between education and organic adoption (Padel, 2001). For example, Läpple and Van Rensburg (2011) discover that higher educated Irish farmers are more likely to adopt organic practices whether the diffusion was at an early, middle, or advanced stage (although they did not find parameter significance). The organic farming to education link may be possibly explained by noting that education has been found to influence initial adoption more than intensification (Battisti et al, 2009). Education may be associated with greater familiarity with and increased trust in formal scientific advances, or it may allow for valuation of scientific evidence that is not implementation specific. Thus, the education-adoption link may not be affected by the reduced embodied scientific content of inputs to organic farming. Moreover, the data in this paper looks at adoption of advanced organic techniques, which may be susceptible to productivity gains through education if any exist. In summary, we expect that more educated farmers will adopt organic techniques more often, but possibly they will not intensify their use at a greater rate than less educated farmers.

As well as affecting technology adoption, education may also alter the use of information. Clearly, education may make it easier to assess the worth of information, and then implement it. Thus, it is less costly to evaluate and use information, so more may be used. Education may also increase familiarity and comfort with the use of information. On the other hand, education may substitute for information if educated farmers are able to form independent judgements of technological issues without guidance from information sources, and so the use of information may decline with education. Many empirical studies do not indicate a strong relation between education and use of specific information sources. For example, Ortmann et al (1993) finds no significant relation of education to the use of consultants by a fairly select group of young, well educated US farmers. A sample from a wider farming group is analysed by Foltz et al (1996), who also find education is unimportant as an influence on consultant use. The results may be specific to use of consultants, rather than information more generally. There are reasons to suspect education's effect would vary by the type of information. If some types of information are highly technical, they might be much more easily processed by well-educated farmers, while less technical information may be less educationally demanding. For less technical information, the ratio of value to cost of use may be more favourable for farmers with less education. Gervais et al (2001) distinguish between demand for different information sources by Canadian farmers, but find education has generally low significance as an influence. Gloy et al (2000) also report generally low significance in their examination of perceived information utility for US farms across various sources, but also find a broadly positive effect of having at least graduated from high school. Just et al (2002) provide some support for the hypothesis that education encourages more technical information use, in that some levels of education are associated with increased use of data (rather than processed information), public information (rather than more processed private information), and formal information (rather than informal information). However, the statistical significances are not high and are not corrected for the number of educational categories, so the evidence is not very strong. To condense our expectations from the theory and empirics, we anticipate that education may be associated with increased use of information, particularly technical information, but that the significance may not be high.

Total agricultural area

Farm size is measured by the area farmed, with all units converted into hectares. In the general diffusion literature, larger enterprises are often proposed to have higher initial adoption rates. Reasons for their earlier adoption are given in Mansfield (1963b). Because of their size, they can benefit from economies of scale in implementation, and are more likely to have resources supporting implementation and diversification. Their size means that conditions amenable to adoption are more likely to arise in them before smaller firms, and replacement of technology units occurs more often because there are more of them in bigger firms. Empirical work has often supported the existence of a positive association between firm size and timing or rate of initial adoption. Amongst others, links have been found for the various coal, steel, brewing, and railway innovations (Mansfield, 1963b); for numerical control machine tools (Romeo, 1975); for data telecommunications (Antonelli, 1985); for computer aided design

(Åstebro, 2002); for IT equipment and collaborative practices (Battisti et al, 2004); and internet use (Battisti et al, 2007).

In the agricultural literature, El-Osta and Morehart (1999) and Abdulai and Huffman (2005) transfer to the farming industry Mansfield's (1963b) theoretical point on the resources of larger enterprises facilitating adoption. Resources might be brought to bear on learning about the technology and setting up new suppliers and buyers. Large fixed costs may also be spread over a greater total production than for small farms. Abdulai and Huffman (2005) make a related point for spreading costs of indivisible technologies. A contrary view whereby larger companies adopt later is presented in Genius et al (2006), who note that smaller farms may be under more financial pressure to innovate. Genius et al (2006) raise a further point specific to organic farming. Small farms are often more dependent on family labour with low opportunity cost. As organic farming is more labour intensive than conventional farming, it is to them a relatively more efficient use of available resources. A further point is made by Padel (2001) who observes that if organic farmers were entrants from urban backgrounds without large inherited landholdings, then organic farms will tend to be smaller than conventional farms.

As with the general empirical literature, the agricultural empirical literature has often shown a positive link between enterprise size and adoption. It has been shown for cow breeding technologies (Khanal and Gillespie, 2011), milking parlours and record keeping systems (El-Osta and Morehart, 1999), cross-breeding (Abdulai and Huffman, 2005), computers on farms (Amponsah, 1995), and pesticide and weedicide (Feder and Slade, 1984). However, the specific character of the technology can modify the relation between size and adoption. Bernues and Herrero (2008) find that use of technologies that allow for rearing animals in smaller areas is inversely related to farm size. Foltz and Lang (2002) find that with labour intensive grazing, increasing farm size is not associated with increased adoption, consistent with the point raised by Genius et al (2006) on labour use for smaller farms. Farm size is not significantly associated with increased organic adoption for Greek farmers in Genius et al (2006), with a negative coefficient on the slightly insignificant link. In Läpple and Van Rensburg (2011), increasing land size is significantly associated with reduced adoption of organics. However, increasing family size is also associated with reduced adoption, challenging the idea that more available family labour increases organic adoption. Läpple and Van Rensburg (2011) explain the discrepancy by postulating a second effect also occurs, that larger families can act as a constraint on business decisions. Padel (2001) notes a trend over time in the size of organic farms in the European Union, with their average size rising from below to above the average size of conventional farms.

The evidence presented indicates that adoption of organic farming in itself may be negatively related to farm size. However, conditional on organic farming adoption, the adoption of organic techniques is plausibly increased by larger farm size. As we are interested in unconditional initial adoption of the techniques, the effect of size on adoption captures both effects at once. We therefore do not have a strong prior expectation on the sign of size.

The effect of enterprise size on adoption intensity is potentially qualitatively different from its effect on initial adoption. Romeo (1975) outlines two possible reasons why intensity may be negatively related to size. Romeo proposes (following Mansfield (1963a)) that smaller enterprises have to invest less in absolute terms to convert to a new technology. Further, their first purchase is generally later, when the risks of adoption are less, so subsequent purchases can happen with less risk than the subsequent purchases of a large company whose initial adoption is early. The former reason is not entirely convincing, as available funds would also be scaled with the enterprise size and economies of scale may be realisable in finance. The latter reason seems more compelling. Antonelli (1985) further observes that intensification could be delayed for bigger firms due to rigid internal management structures and more complex fixed investment (again after Mansfield (1963a)). We could also add (repeating Mansfield (1963a) once again) that a smaller company would be less able to manage multiple internal technologies, so conversion is more likely to be rapid when the initial adoption is made. Another reason could be that conditions are more likely to be uniform over the company.

The empirical evidence on intensification generally supports the existence of a negative relation between enterprise size and intensification. Mansfield (1963) demonstrates the slower intensification of usage of diesel trains replacing steam trains, while Romeo (1975) does the same for machine tools, and Fuentelsaz et al (2003) for automated teller machines. Antonelli (1985) finds longer intensification lags on data telecommunications for large companies, and Battisti et al (2009) discover large companies are not more likely to intensify e-business usage. Genius et al (2006) look at organic farming and show that larger farms are not more likely to intensify their adoption.

The theoretical and empirical evidence suggests that larger farms intensify their organic practices less than smaller farms. We therefore expect the coefficient on farm size in our intensification equation to be negative.

The effect of farm size on information use has also attracted attention in the literature. Gloy et al (2000) comment that salespeople are more likely to call on large farms, so their information is more likely to be perceived as useful. The perception may be a result of the greater exposure to the information, and may arise for other sources whenever supply is sensitive to the size. Gervais et al (2001) suggest that size approximates physical capital and personal characteristics, specifically risk preferences. They do not say that this leads to any particular direction of association between sign and information use. We can also note that information has a public good character and since large farms can use the same information over larger production, it may be anticipated that they would use more of it. The ability to spread costs will be more important if farmers find information acquisition costs to be burdensome, as was found by Foltz et al (1996) in their study of the use and discontinuation of consultant use.

Empirically, the evidence on the effect of farm size on information use provides some support for a negative link when suppliers can raise more revenue from large farms, but otherwise no strong results emerge. In Ortmann et al's (1993) study of US farmers, higher sales are associated with greater expenditure on consultants but the expenditure doesn't rise as quickly as sales. Foltz et al (1996) also find that as sales rise so does the use of consultants among Idaho farmers. Gloy et al (2000) examine the utility of various information sources as reported by US farmers. As farm size rises, the valuation attached to manufacturer salespeople increases as well. However, the valuation of crop and livestock specific publications and other farmers falls. In Gervais et al (2001), farm size doesn't have a significant effect on use of any of the seven information sources they consider.

We do not expect any general links between farm size and information use. However, in the case of information types where income to suppliers rises with the farm size, we anticipate a positive relation. These types may include consultants, agents, suppliers, and buyers.

Full time farming indicator

A further codeterminant in our equations is a dummy variable taking the value of one if the farmer farms or produces full time. Writing on management practices, Battisti and Iona (2009) propose that an enterprise with more diversified output will be likely to adopt a wider range of innovations. However, their proposal may not apply when we are considering a set of innovations, such as organic farming practices, that apply exclusively to one part of production, rather than the full set of innovations used in any employment. The agricultural literature has discussed the role of full time farming and off farm income directly. Off-farm activity may raise finance for technological adoption and create incentives for adoption (of labour saving technologies) by raising the opportunity cost of time (Abdulai and Huffman, 2005; Genius et al, 2006; Koundouri et al, 2006). However, it leaves reduced time for acquiring knowledge and making decisions, so reducing adoption (Abdulai and Huffman, 2005). A full time farmer is better placed to adopt a technology that is time and management intensive (Khanna, 2001).

The empirical evidence on off-farm labour's effect on adoption is mixed. Abdulai and Huffman (2005) find that off-farm labour increases adoption of a crossbred cow. Their study was in Tanzania where extra response of adoption to additional income may be expected. In Khanna (2001) working part time has a positive but insignificant effect on adoption of soil testing and application technologies. However, Khanal and Gillespie's (2011) examination of breeding technologies demonstrates that negative relation between having an off-farm job and adoption, and Koundouri et al (2006) find that rising off-farm income reduces adoption of irrigation equipment. Finally, in Genius et al (2006) off-farm income doesn't significantly change adoption of organic farming.

The outcomes of working part time on adoption seem to be sensitive to the financial and other conditions in which adoption occurs. We do not form any prior expectations of the coefficient sign on the full time working dummy.

There are also plausible theoretical links between working part time and information use. Off farm activity may lead to increased reliance on information to replace experience on the farm (Genius et al, 2006). Off farm activities may also increase the overall complexity of income-earning activities, and raise the value of general management information (Ortmann et al, 1993). On the other hand, the time available for searching out information may diminish. We see few results in the empirical literature to clarify which side of the trade-off is dominant. In Genius et al (2006), information collection either actively or from extension agents is not affected by part time working. Ortmann et al (1993) do not examine off farm work, but look at the percentage of farmers' assets held off-farm. Higher holdings are significantly associated with more use of consultants.

To summarise for our study, we do not form a strong theoretical expectation on the effect of working part time on information use.

Environmental scheme use

We construct a measure of average environmental scheme membership from responses to survey questions on membership of eight individual environmental schemes. The questions ask about membership in the schemes listed in table 3.A1. Non-missing responses to each question are coded one for current membership, two if the farmer will consider membership in the next two years, and three if the farmer will not consider engagement. We calculate a measure of membership as three minus the response for each question when a response is given, and then average over all scheme measures to get our combined scheme membership measure.

Table 3.A1

Environmental schemes used to measure of average environmental scheme membership

Countryside Stewardship Scheme
Entry Level Stewardship
Higher Level Stewardship
Organic Farming Scheme
Environmentally Sensitive Areas
Voluntary Initiative
Single Farm Payment
Other

The measure rises if the farmer is a member of a component scheme, and it rises by slightly less if the farmer is considering membership. There are various ways in which increases in the measure are likely to be associated with adoption of organic farming. Farmers who join schemes may have higher awareness and commitment to environmental matters that is also manifested by adoption of organic farming. Membership may be sought as a means of providing certification of organic farming practices. A scheme member may gain additional motivation from membership, for example from contact with like-minded farmers or earlier adopters, and the motivation may lead to increased adoption. Membership may increase awareness of and access to technology suppliers.

Environmental awareness and concern are theoretically plausible precursors to scheme membership. The empirical literature has examined the links between the two measures of environmental attitude and organic farming adoption. Läpple and Van Rensberg (2011) examine Irish farmers and determine that if a farmer is more concerned by environmental issues, they are significantly more likely to adopt. The increased probability of adoption exists at early and late stages of diffusion In Genius et al (2006), awareness of environmental issues among Greek farmers is associated with increased initial adoption. It is also associated with intensification of use.

We summarise our expectations on environmental scheme membership and adoption. On the basis of theoretical and empirical evidence we expect the two to be positively and significantly related.

Environmental group consultation

A measure of average environmental group consultation is formed from survey questions on consultation of two not-for-profit organisations providing conservation advice and support to farmers. The first of these organisations is called Linking Environment And Farming (LEAF, www.leafuk.org) and the second is the Farming and Wildlife Advisory Group (FWAG, www.fwag.org.uk). The questions ask whether the organisation has ever been consulted, with responses of “yes”, “no”, or “never heard of it”. The average consultation measure is then put equal to zero if neither group has been consulted, 0.5 if only one group has been consulted, and one if both groups have been.

We anticipate that rises in environmental group consultation may be associated with increased organic farming adoption, for similar reasons that environmental scheme use may be. Consultation indicates environmental awareness and concern, increases exposure to environmental messages, and provides information on suppliers. Empirical evidence connecting awareness and concern with adoption was described when we looked at scheme use. Our expectation is that increases in consultation will be associated with increased initial adoption and intensification.

Internet access score

For each farm, a measure of internet access is constructed by linking the farm's region with the average internet access there. Our base farming data from the Rural Economy and Land Use Programme contains information on the area in which the farm is located, but no information on its internet access. We therefore supplement the data with information on internet speed by region from the telecommunications regulator OFCOM (OFCOM, 2013). It provides data on average broadband speed in 2011 by UK local authority area. The measure varies from one to five, with one being the fastest broadband and five being the slowest.

Our base farming data has the first two characters of each farm's postcode, which identifies a postcode area within the UK. The internet data's regional identifier is the local authority, which generally subsumes postcode areas. We manually identify the local authority for each postcode area and include them in the farming data, giving 80 distinct local authorities across the farms. Where there is ambiguity in the postcode between a rural and urban authority (such as the City of Nottingham and Nottinghamshire County), the rural authority is selected. The farming and internet data are then joined by the local authority to allocate each farm the average internet access of its local authority.

The internet may either complement or substitute for information obtained from other sources. On one hand, it may facilitate the acquisition of information from other sources and allow for its clarification and supplementing. The action of internet use may reveal personal characteristics not otherwise controlled for, and that tend towards information acquisition. On the other hand, it may provide information that is also available from other sources, and so act as a substitute for them. Gloy et al (2000) distinguishes between the effect on different source types. They note that information from media sources (with its impersonal nature) would be relatively easy to substitute with internet information, while information from personal sources could be supported by the readier communication.

Empirical evidence has supported the existence of a positive association between internet use and information source adoption. Diekmann et al (2009) look at how intensively Ohio farmers use twenty five information sources, classified into print, broadcast, electronic, and interpersonal sources. They find that internet access is associated with increases in use, and substitution into electronic sources from other sources. Gloy et al (2000) discover that US farmers who use the internet for their business are more likely to believe that a variety of information sources are useful, particularly personal ones. Given the theoretical considerations and empirical findings, we anticipate that better internet access will be associated with increased information use (so there will a negative sign on the internet score coefficient).

Our expectations for all characteristics are collected in table 3.A2.

Table 3.A2

Prior expectations of the effects of characteristics on adoption and information use

Characteristic	Initial adoption	Intensified adoption	Information use
Years of farming	+ / -	+ / -	+ / -
Formal education	+	+ / -	+ (low significance)
Total agricultural area	+ / -	-	+ (consultants, agents, suppliers, and buyers) + / - (others)
Full time farming indicator	+ / -	+ / -	+ / -
Environmental scheme use	+	+	NA
Environmental group consultation	+	+	NA
Internet access score	NA	NA	-

Appendix 3.B

Estimation results for the chemical user, extracrop bio-controller, and weed focussed farmer portfolios

Table 3.B1, part one
Estimated coefficients for information determinants of initial adoption of a chemical user technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.7172***	-1.0124***								
	0.1854	0.1447								
Agents	-0.1839		-1.4165***							
	0.1899		0.4606							
Academia	0.0808			-0.8792						
	0.2326			0.9242						
Suppliers	0.5956***				-1.0581***					
	0.2007				0.113					
Buyers	0.3445					1.8013***				
	0.2183					0.2457				
Farmers	0.1038						-1.0253***			
	0.1877						0.3868			
DEFRA	0.2141							2.0226***		
	0.1862							0.1907		
Farmers Weekly	-0.0648								1.5577***	
	0.1845								0.2873	
Farmers Guardian	0.0712									-0.8484
	0.194									0.5632

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B1, part two

Estimated coefficients for non-information determinants of initial adoption of a chemical user technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0214***	-0.0140**	-0.0186***	-0.0199***	-0.0164***	-0.0109	-0.0227***	-0.0112*	-0.0113*	-0.0216***
	0.008	0.0063	0.0068	0.0072	0.0058	0.007	0.0062	0.0063	0.0068	0.0068
Formal education	-0.0783	0.069	0.0411	0.0101	-0.0523	-0.0725	-0.0205	-0.0584	-0.0522	-0.0711
	0.0879	0.0648	0.0739	0.0852	0.0631	0.0678	0.0693	0.0624	0.0693	0.0776
Hectares	0.0011	0.0006*	0.0009*	0.0012**	0.0007*	0.0008	0.0009*	0.0009*	0.0007	0.0011*
	0.0007	0.0003	0.0005	0.0006	0.0004	0.0005	0.0006	0.0005	0.0005	0.0006
Full time	-0.1213	0.1678	-0.062	-0.0226	-0.0133	-0.1335	0.0055	-0.1277	-0.2422	0.0401
	0.2359	0.1627	0.1749	0.2046	0.1637	0.1784	0.1815	0.1645	0.1873	0.2129
Environ schemes	-0.1014	-0.0939	-0.1724	-0.2305	-0.1426*	-0.1812	-0.153	-0.1439	-0.1648	-0.2135
	0.1741	0.088	0.1372	0.1523	0.0775	0.124	0.122	0.1026	0.1335	0.1463
Environ consults	0.4245*	0.2413	0.4182**	0.4938**	0.2647*	0.3443*	0.3970*	0.3405**	0.4424**	0.5389***
	0.2443	0.1468	0.2072	0.2114	0.1385	0.1764	0.2055	0.1613	0.1884	0.2049
Local adoption	-0.0046	-0.0011	-0.0016	0.0007	0.0007	-0.0066	0.0036	-0.0053	0.0011	0.0061
	0.0085	0.0061	0.0066	0.0077	0.0061	0.0067	0.007	0.0063	0.007	0.0083
Constant	1.3018*	1.8353***	2.2756***	2.3035***	2.6982***	1.4570**	2.6254***	0.5584	1.0028	2.5864***
	0.7717	0.5214	0.629	0.675	0.4669	0.634	0.5575	0.5616	0.6956	0.6224
Rho		0.966	0.8778	0.6351	0.9881	-0.8638	0.8452	-0.9491	-0.8182	0.6276
p-value		0.0187	0.1115	0.2535	0.0728	0.0145	0.0943	0.0025	0.0036	0.1082
(Pseudo) R^2	0.2094									

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. The p-value is for a test of $\rho=0$. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B2

Estimated coefficients for determinants of information use for initial adoption of a chemical user technology

	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0025	-0.0088*	-0.0061	-0.0094	-0.0074	-0.0162***	-0.0008	-0.0107**	-0.0094*
	0.0055	0.005	0.0055	0.0059	0.0051	0.0053	0.0049	0.0051	0.0052
Formal education	0.1542**	0.1606***	0.2490***	-0.0176	0.0635	0.0335	0.0565	0.0522	-0.1199**
	0.0634	0.059	0.0682	0.07	0.0596	0.0624	0.0567	0.058	0.061
Hectares	0.0003	0.0003*	0.0003*	-0.0001	0.0001	0.0000	0.0001	0.0008***	0.0000
	0.0002	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0003	0.0001
Full time	0.2503	-0.0949	0.0542	0.0748	0.1537	0.1142	0.1483	0.4040***	0.4476***
	0.1552	0.1455	0.1593	0.1719	0.1546	0.156	0.1435	0.1488	0.1628
Internet score	0.0817*	0.0524	0.0427	0.0854**	-0.1307***	0.0613	-0.0677*	-0.1054**	0.1577***
	0.0479	0.0479	0.0555	0.0411	0.0484	0.0471	0.0404	0.0478	0.0523
Local adoption	0.0003	-0.0017	-0.0018	0.0003	0.0093	0.006	0.0064	-0.0013	0.0188***
	0.0061	0.0055	0.0062	0.0063	0.0057	0.006	0.0056	0.0059	0.0057
Constant	-0.2431	-0.5449	-1.6255***	0.9645**	-0.2327	0.585	0.1702	0.3927	-0.6252
	0.4089	0.3862	0.4404	0.4326	0.3893	0.4137	0.373	0.3876	0.4077

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by recursive bivariate probit with the initial adoption of the technology jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B3
Marginal effects of using an information sources on initial adoption of a chemical user technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.1020***	0.1348**								
	0.0259	0.0609								
Agents	-0.0261		0.028							
	0.027		0.0234							
Academia	0.0115			0.044						
	0.0331			0.0542						
Suppliers	0.0847***				0.1298*					
	0.0282				0.0682					
Buyers	0.049					0.0579**				
	0.0311					0.0283				
Farmers	0.0148						0.0616			
	0.0267						0.0446			
DEFRA	0.0304							0.0201		
	0.0264							0.0294		
Farmers Weekly	-0.0092								-0.0001	
	0.0262								0.0109	
Farmers Guardian	0.0101									0.0364
	0.0276									0.0265

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B4, part one

Estimated coefficients for information determinants of intensification of a chemical user technology

	All	icc	Agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.2003***	0.2393**								
	0.0652	0.1203								
Agents	0.0261		0.038							
	0.0515		0.1393							
Academia	0.1074**			0.0819						
	0.0546			0.1437						
Suppliers	0.2209***				0.2202*					
	0.0689				0.117					
Buyers	0.1511***					0.2641**				
	0.0516					0.129				
Farmers	-0.0052						0.1142			
	0.0559						0.117			
DEFRA	0.0994*							0.2149		
	0.0547							0.1392		
Farmers Weekly	0.0407								0.2285*	
	0.0555								0.1193	
Farmers Guardian	-0.0123									-0.0191
	0.0521									0.1293

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B4, part two
Estimated coefficients for non-information determinants of intensification of a chemical user technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0042*	-0.0055**	-0.0054**	-0.0052**	-0.0052**	-0.0048**	-0.0050**	-0.0055**	-0.0046**	-0.0057**
	0.0022	0.0022	0.0022	0.0022	0.0022	0.0022	0.0023	0.0022	0.0023	0.0022
Formal education	-0.0241	-0.0183	-0.0101	-0.0116	-0.0073	-0.0129	-0.0108	-0.0107	-0.017	-0.0103
	0.0269	0.0269	0.027	0.0296	0.0264	0.0264	0.0262	0.0264	0.0268	0.027
Hectares	0.0000	0.0001	0.0001	0.0001	0.0001*	0.0001	0.0001*	0.0001	0.0000	0.0001*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Full time	0.0599	0.075	0.0959	0.0925	0.0916	0.0804	0.0889	0.0843	0.0587	0.0959
	0.0667	0.0663	0.0659	0.0659	0.0659	0.0663	0.0659	0.066	0.0682	0.0686
Environ schemes	-0.0726	-0.0941**	-0.1154**	-0.1006**	-0.0971**	-0.1019**	-0.1031**	-0.1122**	-0.1003**	-0.1065**
	0.0471	0.0462	0.0461	0.0462	0.0461	0.0463	0.0463	0.0462	0.0464	0.0463
Environ consults	0.1497**	0.2296***	0.2375***	0.2357***	0.2611***	0.2087***	0.2617***	0.2335***	0.2527***	0.2609***
	0.0651	0.0625	0.0631	0.063	0.062	0.0633	0.0619	0.0625	0.0622	0.0621
Local adoption	0.0003	0.0005	0.0005	0.0005	0.0005	0.0002	0.0004	0.0003	0.0005	0.0005
	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0007
Constant	0.9424***	1.2994***	1.4699***	1.4327***	1.2328***	1.3839***	1.3639***	1.3631***	1.3270***	1.4695***
	0.2138	0.2051	0.1963	0.1924	0.227	0.1942	0.2144	0.2054	0.2027	0.2008
Rho		-0.9351	1	1	1	-0.9378	-0.8927	-0.993	-1	0.9409
p-value		0.7626		0.9632		0.1667	0.7673	0.002	0.9132	0.0342

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. The p-value is for a test of $\rho=0$. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B5

Estimated coefficients for determinants of information use for intensification of adoption of a chemical user technology

	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0026	-0.0075***	0.0034	-0.0092***	-0.007	-0.0160***	-0.0008	-0.0108	-0.0096*
	0.0056	0.0000	0.0141	0.0000	0.0051	0.0053	0.0034	0.0084	0.0052
Formal education	0.1472**	0.0955***	0.3093***	-0.0553***	0.073	0.0252	0.0241	0.1113	-0.1227**
	0.0622	0.0000	0.1039	0.0000	0.0601	0.0604	0.0443	0.0871	0.0609
Hectares	0.0003	0.0001***	0.0002	-0.0001***	0.0001	0.0000	0.0001*	0.0008***	-0.0001
	0.0002	0.0000	0.0008	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
Full time	0.2611*	-0.0613***	0.0412	0.0569***	0.1572	0.1013	0.062	0.4257***	0.4397***
	0.158	0.0000	0.832	0.0000	0.1531	0.1536	0.0998	0.0807	0.1631
Internet score	0.0483	0.0606***	0.0713	0.0673***	-0.1182**	0.0122	-0.0073	0.0289	0.1524***
	0.0588	0.0000	0.0959	0.0000	0.0553	0.055	0.0287	0.1589	0.056
Local adoption	0.0000	0.0006***	-0.0008	0.0000***	0.0026*	0.0016	0.0014	0.001	0.0059***
	0.0016	0.0000	0.0136	0.0000	0.0014	0.0015	0.0016	0.0012	0.0015
Constant	-0.1177	-0.4428***	-2.1365**	1.2229***	-0.3253	0.7646*	0.1785	-0.3071	-0.6137
	0.4281	0.0000	0.9025	0.0000	0.4021	0.4131	0.282	0.9466	0.4133

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B6
Marginal effects of using an information sources on intensification of adoption of a chemical user technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.6613***	0.7368								
	0.2159	3.1633								
Agents	0.0863		0.1253							
	0.1701		0.46							
Academia	0.3546**			0.2751						
	0.1805			0.4907						
Suppliers	0.7294***				0.6767**					
	0.2282				0.335					
Buyers	0.4987***					0.9015*				
	0.1709					0.4603				
Farmers	-0.0173						0.3687			
	0.1846						0.4284			
DEFRA	0.3280*							0.6863		
	0.1807							0.4336		
Farmers Weekly	0.1343								0.7287**	
	0.1832								0.37	
Farmers Guardian	-0.0406									-0.0629
	0.1721									0.4247

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B7, part one

Estimated coefficients for information determinants of initial adoption of an extracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.3281**	-0.3864								
	0.1522	1.6								
Agents	0.2242		-0.7926							
	0.1422		0.7493							
Academia	-0.3162**			-0.9085						
	0.1584			0.7287						
Suppliers	0.2643				-1.2754***					
	0.1705				0.1398					
Buyers	0.0746					1.5687***				
	0.1483					0.0967				
Farmers	0.1831						-0.8182			
	0.148						0.6151			
DEFRA	0.2554*							1.6854***		
	0.1419							0.2011		
Farmers Weekly	-0.2042								1.4101***	
	0.1467								0.2027	
Farmers Guardian	0.1274									-0.5984
	0.1451									0.5962

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B7, part two

Estimated coefficients for non-information determinants of initial adoption of an extracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.007	-0.0082	-0.0095*	-0.0094*	-0.0099**	-0.0002	-0.0125**	-0.0056	-0.0011	-0.0100*
	0.0059	0.0056	0.0052	0.0055	0.0049	0.0049	0.0059	0.005	0.0051	0.0055
Formal education	0.0474	0.071	0.0888	0.1027	0.0124	-0.0157	0.0497	0.0082	0.0153	0.0139
	0.0678	0.1012	0.0692	0.0761	0.0575	0.0545	0.0609	0.0577	0.0575	0.0704
Hectares	0.0005*	0.0004*	0.0005**	0.0005*	0.0002	0.0003	0.0004	0.0002	0.0001	0.0004
	0.0003	0.0002	0.0002	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003
Full time	0.3169*	0.3495**	0.2536	0.3288**	0.2449*	0.1002	0.3197**	0.1794	0.0374	0.3797**
	0.1699	0.1703	0.1873	0.1604	0.1466	0.14	0.1574	0.1475	0.1537	0.1644
Environ schemes	0.4413***	0.3949**	0.3124**	0.3569***	0.2619**	0.2568***	0.3421**	0.2996***	0.3040***	0.3718***
	0.1223	0.1701	0.1328	0.117	0.1028	0.0867	0.1373	0.0946	0.0911	0.1167
Environ consults	1.0990***	1.0269***	0.9116***	1.1301***	0.7717***	0.6819***	0.9612***	0.8392***	0.8547***	1.0652***
	0.192	0.3658	0.3101	0.2074	0.1572	0.1304	0.2829	0.169	0.1664	0.2029
Local adoption	-0.008	-0.0046	-0.0042	-0.0044	-0.0025	-0.0115*	-0.0015	-0.0094	-0.0016	0.0016
	0.0077	0.0074	0.0069	0.0073	0.0066	0.0062	0.0075	0.0066	0.0066	0.0093
Constant	-1.8186***	-0.8027	-0.5145	-0.8967*	0.6415	-1.0134***	-0.2078	-1.6375***	-1.5813***	-0.6525
	0.5562	1.2427	0.6413	0.4818	0.519	0.3929	0.8875	0.4112	0.4202	0.5937
Rho		0.4675	0.6756	0.4307	0.9496	-0.9818	0.6664	-0.8764	-0.8632	0.5061
p-value		0.6678	0.2954	0.3675	0.0664	0.076	0.234	0.0174	0.0017	0.2155
(Pseudo) R^2	0.1802									

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. The p-value is for a test of ρ=0. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B8

Estimated coefficients for determinants of information use for initial adoption of an extracrop technology

	icc	agents	academe	Supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0027	-0.0082	-0.0057	-0.0087	-0.0054	-0.0161***	-0.0017	-0.0110**	-0.0093*
	0.0055	0.005	0.0055	0.0057	0.0052	0.0053	0.005	0.0051	0.0052
Formal education	0.1447**	0.1564***	0.2419***	-0.0348	0.0893	0.0263	0.0515	0.0571	-0.1196*
	0.0624	0.0602	0.0675	0.0654	0.0589	0.0602	0.0573	0.0577	0.0612
Hectares	0.0003	0.0003*	0.0003*	-0.0001	0.0001	0.0000	0.0001	0.0007***	-0.0001
	0.0002	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0002	0.0001
Full time	0.2613*	-0.0916	0.0556	0.0155	0.129	0.0806	0.1318	0.3805**	0.4632***
	0.1576	0.1461	0.1599	0.1629	0.1508	0.1567	0.145	0.1483	0.1645
Internet score	0.0645	0.0307	0.035	0.0696	-0.0734*	0.037	-0.0525	-0.0933**	0.1463***
	0.0582	0.0572	0.0572	0.0429	0.0387	0.0492	0.0442	0.0447	0.0526
Local adoption	-0.0006	-0.0007	-0.0015	-0.004	0.0117*	0.0059	0.0062	-0.0026	0.0234***
	0.0073	0.0064	0.0071	0.0078	0.0067	0.0069	0.0065	0.0067	0.0067
Constant	-0.153	-0.4961	-1.5991***	1.1425***	-0.545	0.7235*	0.206	0.3881	-0.5982
	0.4253	0.4047	0.435	0.4186	0.3841	0.4079	0.3756	0.3787	0.4089

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by recursive bivariate probit with the initial adoption of the technology jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B9
Marginal effects of using an information sources on initial adoption of an extracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.0864**	0.1332**								
	0.0396	0.0561								
Agents	0.059		0.0985**							
	0.0373		0.0423							
Academia	-0.0833**			-0.0515						
	0.0413			0.0339						
Suppliers	0.0696				0.0587					
	0.0446				0.0708					
Buyers	0.0196					0.0752***				
	0.039					0.0243				
Farmers	0.0482						0.0821**			
	0.0389						0.0379			
DEFRA	0.0673*							0.0959***		
	0.0371							0.0316		
Farmers Weekly	-0.0538								-0.0248	
	0.0384								0.0223	
Farmers Guardian	0.0335									0.0746***
	0.0381									0.0259

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B10, part one

Estimated coefficients for information determinants of intensification of an extracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.2238**	0.2684								
	0.1035	0.1749								
Agents	0.0295		0.0948							
	0.0811		0.178							
Academia	-0.05			-0.0483						
	0.0881			0.1912						
Suppliers	0.0888				0.0915					
	0.1009				0.0971					
Buyers	0.0297					0.0492				
	0.0821					0.1341				
Farmers	-0.0321						0.009			
	0.0855						0.1519			
DEFRA	0.0877							0.089		
	0.0859							0.1874		
Farmers Weekly	-0.1149								-0.0406	
	0.0846								0.1767	
Farmers Guardian	0.1586**									0.1747
	0.0809									0.1576

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B10, part two

Estimated coefficients for non-information determinants of intensification of an extracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0016	-0.0019	-0.0017	-0.0021	-0.0019	-0.0019	-0.002	-0.0019	-0.0022	-0.0014
	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0036	0.0035
Formal education	0.0458	0.0271	0.0341	0.0416	0.0384	0.0373	0.0376	0.0377	0.0383	0.0485
	0.0442	0.0435	0.0438	0.0455	0.0427	0.0427	0.0426	0.0427	0.0429	0.0436
Hectares	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Full time	0.1293	0.1338	0.1599	0.1553	0.1549	0.1521	0.1544	0.1492	0.1612	0.1311
	0.1066	0.1054	0.105	0.1048	0.1047	0.105	0.1049	0.105	0.1077	0.1071
Environ schemes	0.2264***	0.2296***	0.2096***	0.2125***	0.2174***	0.2160***	0.2146***	0.2137***	0.2093***	0.2259***
	0.0814	0.0801	0.0799	0.08	0.0799	0.08	0.0801	0.08	0.0801	0.0803
Environ consults	0.4928***	0.5119***	0.5286***	0.5556***	0.5504***	0.5390***	0.5516***	0.5319***	0.5555***	0.5421***
	0.1018	0.0981	0.0988	0.0979	0.0971	0.0991	0.0971	0.0982	0.0973	0.0971
Local adoption	-0.0057**	-0.0045*	-0.0045*	-0.0045*	-0.0045*	-0.0046*	-0.0045*	-0.0047*	-0.0046*	-0.0054**
	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026	0.0027	0.0026	0.0027
Constant	-1.0072***	-0.8890**	-0.7321**	-0.7063**	-0.7974**	-0.7238**	-0.7160**	-0.7527**	-0.6729*	-0.8330**
	0.3619	0.3466	0.3355	0.3301	0.3451	0.3319	0.3528	0.3461	0.3487	0.3417
ρ		-0.9291	0.8737	1	1	0.8531	0.8432	0.9949	-1	0.8725
p-value		0.6703	0.9617	0.9039		0.965	0.9634	0.0008		0.8656

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. The p-value is for a test of $\rho=0$. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B11
Estimated coefficients for determinants of information use for intensification of adoption of an extracrop technology

	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0026	-0.0077	-0.0051	-0.0089***	-0.0069	-0.0159***	-0.0013	-0.0137***	-0.0097*
	0.0055	0.005	0.0539	0.0000	0.0051	0.0053	0.0031	0.0000	0.0052
Formal education	0.1480**	0.1513**	0.2472**	-0.0475***	0.0738	0.0246	0.0151	0.0580***	-0.1274**
	0.0622	0.0597	0.1243	0.0000	0.0603	0.0604	0.0373	0.0000	0.0604
Hectares	0.0003	0.0003*	0.0003	-0.0001	0.0001	0.0000	0.0001**	0.0007***	-0.0001
	0.0002	0.0002	0.0007	2.89E+09	0.0001	0.0001	0.0001	0.0000	0.0001
Full time	0.2601*	-0.0956	0.0694	0.0768***	0.1565	0.1021	0.0453	0.3832***	0.4386***
	0.1577	0.1473	0.6148	0.0000	0.1532	0.1536	0.088	0.0000	0.1623
Internet score	0.0482	-0.0067	0.0274	0.0550***	-0.1205**	0.0103	-0.0065	-0.0268***	0.1336**
	0.0572	0.0522	0.5309	0.0000	0.0546	0.0534	0.0257	0.0000	0.0544
Local adoption	0.0009	0.0009	-0.0003	0.0002***	0.0079**	0.0041	0.0046	-0.0016***	0.0130***
	0.0041	0.0037	0.0042	0.0000	0.0037	0.0039	0.0043	0.0000	0.0037
Constant	-0.1345	-0.3948	-1.5603	1.1694***	-0.335	0.7733*	0.2333	0.2980***	-0.4974
	0.4251	0.3944	1.0216	0.0000	0.4005	0.4099	0.2378	0.0000	0.4064

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B12

Marginal effects of using an information sources on intensification of adoption of an extracrop technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.3016**	0.3341								
	0.14	0.2292								
Agents	0.0398		0.1277							
	0.1092		0.2406							
Academia	-0.0674			-0.0644						
	0.1187			0.2531						
Suppliers	0.1196				0.1198					
	0.136				0.1235					
Buyers	0.04					0.0666				
	0.1106					0.183				
Farmers	-0.0432						0.0121			
	0.1152						0.204			
DEFRA	0.1182							0.1181		
	0.1159							0.2338		
Farmers Weekly	-0.1548								-0.055	
	0.1142								0.1112	
Farmers Guardian	0.2138*									0.2411
	0.1093									0.2234

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B13, part one

Estimated coefficients for information determinants of initial adoption of a weed focussed farmer technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.5163***	-1.1615***								
	0.1751	0.0936								
Agents	-0.1121		1.5503***							
	0.1749		0.2478							
Academia	-0.3337*			-2.0810***						
	0.1912			0.3681						
Suppliers	0.158				-1.2232***					
	0.1964				0.1333					
Buyers	0.4724**					2.0324***				
	0.1984					0.1432				
Farmers	0.3331*						-1.1297***			
	0.1729						0.2155			
DEFRA	0.0982							1.9547***		
	0.1706							0.2143		
Farmers Weekly	0.1087								1.7767***	
	0.1679								0.2406	
Farmers Guardian	0.0946									-1.2329***
	0.1776									0.4151

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B13, part two

Estimated coefficients for non-information determinants of initial adoption of a weed focussed farmer technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0011	-0.0042	0.002	-0.0043	-0.0078	0.0056	-0.0112**	-0.0016	0.0037	-0.0083
	0.007	0.005	0.0056	0.0053	0.0054	0.0048	0.0055	0.0053	0.0057	0.006
Formal education	0.0553	0.1260**	-0.047	0.1797**	0.0197	-0.018	0.0628	0.0052	0.0265	-0.0003
	0.0824	0.0586	0.0682	0.0714	0.0642	0.057	0.063	0.0619	0.0646	0.0741
Hectares	-0.0002	0.0000	-0.0002*	0.0001	-0.0001	-0.0001*	-0.0001	-0.0001	-0.0002*	-0.0001
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Full time	0.2654	0.3595**	0.2861*	0.2637	0.2519	0.0536	0.2830*	0.1362	0.0222	0.4325**
	0.1957	0.1424	0.1618	0.1687	0.1571	0.1419	0.1589	0.1642	0.1696	0.1683
Environ schemes	0.0499	0.0068	-0.0257	-0.0005	-0.0328	0.0420*	-0.0098	0.0035	-0.012	-0.036
	0.1506	0.0516	0.0967	0.1006	0.0848	0.0247	0.0865	0.0852	0.1046	0.1148
Environ consults	0.5125**	0.2013***	0.3841**	0.3981	0.3619**	0.2494***	0.3578**	0.3325*	0.3948**	0.5018***
	0.2251	0.0676	0.1791	0.2843	0.1478	0.0894	0.1782	0.1819	0.1744	0.1843
Local adoption	-0.0063	-0.0027	-0.0008	-0.0018	-0.0006	-0.0089*	0.0011	-0.0057	-0.0004	0.006
	0.008	0.0056	0.0061	0.0061	0.0061	0.0053	0.0062	0.0059	0.0064	0.0071
Constant	-0.2329	1.0115***	0.0096	0.5356	1.8538***	-0.1344	1.4417***	-0.5109	-0.5143	1.2323**
	0.6814	0.3833	0.4742	0.4535	0.4575	0.3709	0.4604	0.4378	0.5156	0.514
ρ		1	-0.8974	0.967	0.9468	-1	0.9212	-0.9551	-0.8983	0.8046
p-value		0.9859	0.0123	0.1922	0.0044	0.9868	0.0165	0.0157	0.0023	0.0277
(Pseudo) R^2	0.126									

The determined variable is a binary variable for adoption of any technology in the portfolio of technologies. The first column is estimated by probit estimation, treating all information variables as exogenous. The remaining columns are estimated by recursive bivariate probit with the information variable at the top of the column jointly determined. The p-value is for a test of $\rho=0$. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B14

Estimated coefficients for determinants of information use for initial adoption of a weed focussed farmer technology

	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.004	-0.0064	-0.0090*	-0.0099*	-0.0046	-0.0164***	-0.0021	-0.0083	-0.0084
	0.0053	0.0051	0.0052	0.006	0.005	0.0053	0.0049	0.0052	0.0052
Formal education	0.1684***	0.1437**	0.2150***	-0.0401	0.0902	0.0221	0.026	0.0596	-0.0989
	0.0648	0.0599	0.0649	0.0684	0.0592	0.0614	0.0579	0.0576	0.0637
Hectares	0.0001	0.0004***	0.0002*	-0.0001	0.0001	0.0000	0.0002	0.0009***	-0.0001
	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0002	0.0002	0.0002
Full time	0.2126	-0.1427	0.0979	0.0444	0.1862	0.1151	0.1322	0.4051***	0.4584***
	0.1518	0.1505	0.1562	0.1699	0.149	0.1566	0.1428	0.1492	0.159
Internet score	0.0795***	-0.0820**	0.0943**	0.1247***	-0.0968***	0.0907**	-0.0693*	-0.1249***	0.1998***
	0.0299	0.0411	0.0445	0.0449	0.0239	0.0417	0.0399	0.0445	0.0511
Local adoption	-0.0008	-0.0012	-0.0018	0.0004	0.0062	0.0048	0.004	-0.0024	0.0167***
	0.006	0.0055	0.0057	0.0065	0.0055	0.0059	0.0054	0.0056	0.0057
Constant	-0.1612	-0.1496	-1.5677***	0.9838**	-0.5026	0.5681	0.3425	0.3321	-0.8048*
	0.4005	0.3837	0.4225	0.4503	0.3576	0.4064	0.3667	0.3829	0.4146

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by recursive bivariate probit with the initial adoption of the technology jointly determined. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B15
Marginal effects of using an information sources on initial adoption of a weed focussed farmer technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.0862***	0.1079*								
	0.0289	0.0611								
Agents	-0.0187		0.0139							
	0.0292		0.0154							
Academia	-0.0557*			-0.0053						
	0.0318			0.1247						
Suppliers	0.0264				0.0579					
	0.0328				0.0689					
Buyers	0.0788**					0.095				
	0.0332					0.0719				
Farmers	0.0556*						0.0846**			
	0.0288						0.042			
DEFRA	0.0164							0.0342		
	0.0285							0.0348		
Farmers Weekly	0.0181								0.0135	
	0.028								0.0206	
Farmers Guardian	0.0158									0.0468***
	0.0296									0.0146

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B16, part one

Estimated coefficients for information determinants of intensification of a weed focussed farmer technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.0978	0.1674								
	0.0724	0.1164								
Agents	0.0196		0.1042							
	0.0588		0.1129							
Academia	0.0157			0.0766						
	0.0633			0.062						
Suppliers	0.0363				0.1024					
	0.0746				0.0716					
Buyers	0.2079***					0.2571**				
	0.0589					0.1059				
Farmers	0.0331						0.1257			
	0.064						0.1034			
DEFRA	0.1263**							0.1873***		
	0.0627							0.059		
Farmers Weekly	-0.0216								0.1316	
	0.0626								0.1152	
Farmers Guardian	0.0969*									0.1308
	0.0587									0.1061

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B16, part two
Estimated coefficients for non-information determinants of intensification of a weed focussed farmer technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0016	-0.0026	-0.0024	-0.0027	-0.0025	-0.0022	-0.0021	-0.0026	-0.0024	-0.0023
	0.0025	0.0025	0.0025	0.0025	0.0025	0.0025	0.0025	0.0025	0.0025	0.0025
Formal education	0.0204	0.0157	0.0179	0.017	0.0232	0.0194	0.0205	0.0215	0.0159	0.0287
	0.0309	0.0307	0.0307	0.0304	0.0302	0.0302	0.0301	0.0302	0.0303	0.0307
Hectares	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Full time	0.1259	0.1492*	0.1664**	0.1610**	0.1611**	0.1484*	0.1569**	0.1530**	0.1386*	0.1431*
	0.0776	0.0769	0.0766	0.0764	0.0765	0.0767	0.0765	0.0765	0.0782	0.0779
Environ schemes	0.017	0.0045	-0.0107	-0.002	-0.0008	0.0031	0.0035	-0.0067	-0.0054	0.0037
	0.0553	0.054	0.0538	0.0539	0.0539	0.0541	0.0541	0.0539	0.054	0.054
Environ consults	0.1505**	0.2295***	0.2317***	0.2408***	0.2516***	0.1907***	0.2492***	0.2200***	0.2473***	0.2469***
	0.074	0.0713	0.0717	0.0714	0.0706	0.072	0.0705	0.0712	0.0708	0.0706
Local adoption	-0.0018*	-0.0013	-0.0013	-0.0013	-0.0013	-0.0015	-0.0014	-0.0014	-0.0012	-0.0016
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Constant	0.4112*	0.6274***	0.7181***	0.7362***	0.6360***	0.6593***	0.6234***	0.6449***	0.6903***	0.6565***
	0.2486	0.2357	0.2273	0.2239	0.2369	0.2254	0.2409	0.2265	0.2363	0.2314
ρ		-0.9686	-0.9395	-1	-1	-0.9059	-0.877	0.8145	-1	0.9109
p-value		0.2356	0.6513	0.982	0.9844	0.7614	0.886	0.9956		0.3987

The determined variable is a count of the number of technologies adopted in the portfolio. The first column is estimated by Poisson estimation, treating all information variables as exogenous. The remaining columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable at the top of the column. The p-value is for a test of $\rho=0$. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B17

Estimated coefficients for determinants of information use for intensification of adoption of a weed focussed farmer technology

	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
Years farming	-0.0031	-0.0078	-0.0117	-0.011	-0.0072	-0.0160***	-0.002	-0.0131***	-0.0097*
	0.0067	0.005	0.0307	0.0764	0.0051	0.0053	0.005	0.0000	0.0052
Formal education	0.1470**	0.1490**	0.1679	-0.0748	0.0717	0.0243	0.05	0.0271***	-0.1244**
	0.0609	0.0614	0.4513	2.8294	0.0602	0.0604	0.0587	0.0000	0.0604
Hectares	0.0003*	0.0003*	0.0001	-0.0001	0.0001	0.0000	0.0001	0.0007	-0.0001
	0.0002	0.0002	0.0005	0.0023	0.0001	0.0001	0.0001	1.03E+09	0.0001
Full time	0.267	-0.0933	0.3325	0.1474	0.1597	0.1039	0.132	0.3423***	0.4350***
	0.1664	0.1481	0.6056	6.8215	0.153	0.1534	0.1483	0.0000	0.1622
Internet score	0.0487	-0.0055	0.0222	0.1177	-0.1151**	0.0119	-0.019	-0.0656***	0.1341**
	0.0612	0.0526	0.4487	5.7113	0.0544	0.0536	0.0523	0.0000	0.0546
Local adoption	-0.0008	-0.0004	0.0011	0.0000	0.0023	0.0013	0.0014	-0.0019***	0.0067***
	0.0022	0.002	0.0082	0.6782	0.002	0.002	0.002	0.0000	0.002
Constant	-0.0945	-0.3659	-1.2134	1.0908	-0.2818	0.7955*	0.1313	0.5985***	-0.4856
	0.4275	0.4016	3.6538	29.1286	0.3992	0.4097	0.3926	0.0000	0.4062

The determined variable is a binary variable for use of the information at the top of the column. The columns are estimated by a Poisson technology adoption model with a treatment effect from the information variable. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

Table 3.B18

Marginal effects of using an information sources on intensification of adoption of a weed focussed farmer technology

	All	icc	agents	academe	supplier	buyers	farmers	defra	fweekly	fguard
ICC	0.249	0.4063								
	0.1845	7.62E+24								
Agents	0.0498		0.2659							
	0.1497		14.1719							
Academia	0.0399			0.1983						
	0.1612			0.1635						
Suppliers	0.0923				0.2525					
	0.1898				0.1708					
Buyers	0.5292***					0.6750**				
	0.1507					0.2893				
Farmers	0.0844						0.3122			
	0.1629						0.2509			
DEFRA	0.3215**							0.4626***		
	0.1598							0.1416		
Farmers Weekly	-0.055								0.328	
	0.1592								0.2815	
Farmers Guardian	0.2466*									0.3386
	0.1497									0.2757

The entries are the differences in adoption probability when the information at the top of the column is used compared with when it is not used. The other variables are held at their mean. * denotes ten percent significance, ** denotes five percent significance, and *** denotes one percent significance.

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Chapter 4

Introduction of innovations during the 2007-8 financial crisis: US companies compared with universities

4.1 Introduction

The 2007-8 financial crisis marked a period of financial decline and disruption unusual since 1945 (Reinhart and Reinhart (2010), figure 1). Defaults on loans in the US subprime mortgage market resulted directly and indirectly in losses to lenders and their resulting bankruptcies (Acharya et al, 2009; Brunnermeier, 2009). The cost of lending rose across many debt instruments (Acharya et al, 2009), and the crisis spread to international financial markets through losses and reduced availability of external finance (Claessens et al, 2010).

The resulting real economic disruption affected industrial innovation. Paunov (2012) finds that many Latin American companies stopped innovation projects, while Archibugi et al (2013b) and Filippetti and Archibugi (2011) determine broad innovation expenditure reductions for European companies. Laperche et al's (2011) examination of French businesses finds them streamlining and prioritising R&D during the crisis. Makonnen (2013) looks at European government R&D expenditures by innovation type, and shows that governments tended to reduce their budgets during the crisis.

If funding sources suffered losses in the crisis, or if their means of transferring funds to recipients were interrupted, the cost of finance would have risen and institutions dependent on it would have found their operations curtailed (Campello et al, 2010; Dell'Ariccia et al, 2008;

Kroszner et al, 2007). Research on the 2007-8 crisis' effect on innovation has examined the role of dependence on external finance in passing. Paunov's (2012) investigation of Latin American companies uses indicator variables for corporate access to public funding (which significantly reduces the chance of discontinuing an innovation project) and private external funding (which has no significant effect). Archibugi et al's (2013a) European study uses an indicator variable for whether companies considered availability to be an innovation obstacle prior to the crisis. It has a negative insignificant effect on innovation expenditure growth before the crisis, and positive insignificant effect during it. Filippetti and Archibugi (2011) examine behaviour of an ordinal variable indicating whether European firms moved from decreasing innovation investment to maintaining or increasing it during the crisis (or other permutations of this movement). They find that in countries with large national private credit markets there was a tendency to move from declining investment to increasing investment during the crisis, and interpret the result as showing that the financial system depth counteracts the effect of the financial crisis.

In this paper we address more fully questions about whether necessity and ability to attract funding had a major effect on innovation during the crisis. How did US company innovation respond to external funding requirements during the crisis? What was the response of US university innovation? How did their innovation respond to asset intangibility, a measure of the ability to attract external funding?

To answer these questions, we examine the funding relations that financiers have with companies and universities, and how they are affected by the crisis. We find that the change during the crisis in aggregate R&D funding to companies and universities can be used to predict how their innovation responds to external funding dependence. We also determine the relation between asset intangibility and innovation for both types of innovator. The results are used to predict that when US companies are undertaking innovation, the dependence of a class of project on external finance does not significantly change output from that class during the crisis. By contrast, when universities are innovating, more externally dependent classes have increased output during the crisis. A further prediction is that if a project class has a higher ratio of intangible to total assets, then its innovative output will increase during the crisis for university innovators.

We test our hypotheses by examining how predicted patent counts change during the crisis for each innovator type. A database is constructed by joining US patent data with Compustat data, in which the unit of analysis is patent counts in each patent class. The construction allows us to associate measures of external funding dependence, R&D intensity, and other financial quantities to specific innovation classes and their statistics. The empirical results are broadly consistent with the theoretical predictions. We use our parameter estimates to investigate the effect of US company innovation responding to the crisis in the same way as US university innovation, but acting on the same portfolio of US company innovation projects, and vice versa. US company responses are associated with more patenting than US university responses, acting both through financial and non-financial effects.

Section 4.2 looks at aggregate innovation funding to US companies and universities, section 4.3 gives our theoretical framework, section 4.4 describes our data, section 4.5 gives our empirical method, section 4.6 presents our results, section 4.7 looks at counterfactuals, and section 4.8 concludes.

4.2 Aggregate innovation funding before and during the crisis

4.2.1 Funding sources

In 2008, total R&D expenditures in the US were $404 billion, or 2.8 percent of GDP (National Science Board (2012), appendix tables 4-1 and 4-44). US business R&D alone accounted for 1.7 percent of GDP, with government accounting for a further 0.8 percent of GDP. Universities and colleges invested 0.1 percent of GDP from their own funds, with smaller investments from non-profit and foreign sources making up the balance.

Industrial R&D is mainly self-funded by industry, with industrial self-funding accounting for around 90 percent of total expenditure throughout the 2000s (National Science Board (2012), appendix table 4-3). Government funding rose slightly to 13 percent in 2008 and 14 percent in 2009, but remained at historically low levels having exceeded 50 percent throughout most of the 1960s.

By comparison, around two thirds of funding for university R&D came from government in the 2000s, and industry only provided around six percent (National Science Board (2012), appendix table 4-3). Internal university and college monies accounted for about a fifth of the total, with non-profit funding outstripping industrial funding in the final years of the decade. The funding shares were quite stable.

4.2.2 The effect of the financial crisis

Many US banks and financial institutions faced large declines in their capital reserves during the 2007-8 financial crisis. Debt defaults were common, credit lines were quickly used up by borrowers, and short-term creditors to banks withdrew their lending (Ivashina and Scharfstein, 2010). As a consequence, a number became bankrupt, and others were severely financially compromised. Regaining sufficient reserves became important for maintaining an acceptable level of bankruptcy risk and to meet regulatory requirements. The opportunity cost of loaning new money therefore increased sharply. The increased difficulty in raising finance is manifested in aggregate data: bank loans to the corporate sector fell sharply from the middle of 2007 (Ivashina and Scharfstein, 2010), and a precipitous decline was also observed in venture capital funding (OECD, 2009).

Government finances were also severely impacted by the financial crisis. Nevertheless, despite large deficits developed country governments generally provided substantial fiscal stimuli over the crisis period (OECD (2009), figure 5). In the US, the total fiscal package between 2008 and 2010 exceeded five percent of 2008 GDP. Specific funds for innovative investment were made available through the American Recovery and Reinvestment Act (ARRA, 2009) which was passed in February 2009. The occurrence of an increase in government support for industrial R&D at the same time as a substantial downturn in industry's own funding was unique in the period since 1953 (National Science Board (2012), appendix table 4-3).

Industry self-funding for industrial R&D underwent a large decline in 2009 at an annual rate of 5.5 percent, marking the second largest percentage decline since the 1950s (National Science Board (2012), appendix table 4-3). The absolute level remained near historically record levels. Government expenditure in 2008 and 2009 rose with fiscal measures including the American Recovery and Reinvestment Act, but was still far less than industrial funding. The extra government spending was not sufficient to offset the decline in industrial expenditure in 2009. Nevertheless, total R&D funding to industry in 2009 was at its second highest level ever.

4.3 Theoretical framework

4.3.1 Corporate innovation during the crisis

Innovation can be expensive (DiMasi et al, 2003; Adams and Brantner, 2006; DiMasi and Grabowski, 2007), time-consuming (Griffin, 1997), and risky (Cooper and Kleinschmidt, 1995). It may require substantial financing over extended periods in the presence of high risk. Some companies may be able to use internal funds to finance their R&D, but many will not have sufficient available assets and will have to seek external financing for innovation. There are a number of difficulties for a commercial external funding source that are liable to restrict the availability of external finance, or at least make it more expensive than internal finance (Hall, 2002). One problem is information asymmetry between investors and innovators. Because innovation is usually technically demanding, and because innovators often want to preserve secrecy to protect their ideas from rivals, investors generally know less about the projects than the innovators. Thus, a lemons market (Akerlof,

1970) can emerge where investors make higher charges than the better innovators will accept, and the market shrinks.

Financial markets connect investors with fund recipients and can mitigate these informational problems (Rajan and Zingales, 1998). Expert intermediaries operate in financial markets, and they can monitor agent behaviour more closely and enforce better corporate governance. Financial markets often require companies operating on them to follow accounting and disclosure rules, and adopt behavioural standards. These requirements may improve investor knowledge about the companies.

A financial crisis can affect the ability of companies to finance themselves on a commercial basis. In the 2007-8 crisis, funds available from commercial sources were reduced by large scale defaults experienced against their portfolios particularly from US sub-prime mortgages (Calomiris, 2008), which resulted in reduction of revenue streams either directly or through counterparty exposure. The inability to use these assets as collateral reduced the sources' borrowing ability and so the cost of funds available for investment (Acharya et al, 2009; Brunnermeier, 2009; Gorton, 2009). In addition to contraction in the available stock of funding, potential innovators may be less attractive as recipients of funding due to a concurrent recession. The value of monitoring to information intermediaries may be reduced in a depressed market and the credibility of their monitoring may fall for potential investors (Holmström and Tirole, 1997), so increasing the uncertainty associated with investment.

To elaborate on the consequences of these considerations, it is helpful to consider the problems solved by investors and managers considering investment in a project. A private investor deciding on whether to invest in the project during the crisis expects to receive an immediate utility (net of investment cost) of

$$\mu - \Sigma + \varepsilon$$

where μ is the net income from investment, Σ is a measure of the risk from investment due to the crisis interrupting normal market information provision and so leading to ignorance about managerial quality, and ε is an error term with distribution function $f(\varepsilon)$. The crisis risk Σ declines with a rise in T, the level of tangible assets available as collateral to protect against the consequences of imperfect information, so $d\Sigma / dT < 0$. Investment occurs if

$$\mu - \Sigma + \varepsilon > 0$$

or

$$\varepsilon > \Sigma - \mu .$$

The manager who has perfect information about their own managerial quality would act on behalf of the investor and invest if

$$\varepsilon > -\mu .$$

Thus, the excess in investment by managers over external investors during the crisis occurs in the region given by

$$\Sigma - \mu \geq \varepsilon > -\mu \qquad (4.1)$$

This is the region in which a project that had to be entirely externally financed would not be given approval, while the same project that was entirely internally financed would result in investment.

Prior to the crisis, the market informational provision functions normally, and so the investor faces no crisis risk and $\Sigma = 0$. They receive an immediate net utility from investment of

$\mu_b + \varepsilon$

where μ_b is the net income from investment before the crisis. Since there is a recession at the same time as the financial crisis, $\mu_b > \mu$. Investment occurs if

$$\varepsilon > -\mu_b.$$

Investment occurs before the crisis but not during it if

$$\Sigma - \mu \geq \varepsilon > -\mu_b,$$

which happens with probability $\int_{-\mu_b}^{\Sigma-\mu} f(\varepsilon)d\varepsilon$. As we saw in section 4.2, there was a small change in observed company investment during the crisis relative to investment before it, so this probability is small.

From equation (4.1), the probability that a manager invests but an investor does not invest is $\int_{-\mu}^{\Sigma-\mu} f(\varepsilon)d\varepsilon$. Since $\mu_b > \mu$, it follows that

$$\int_{-\mu_b}^{\Sigma-\mu} f(\varepsilon)d\varepsilon > \int_{-\mu}^{\Sigma-\mu} f(\varepsilon)d\varepsilon > 0$$

and so there is a very small probability that a project would be financed if internal finance is available but not financed if external finance is necessary. It follows that there is a very small negative change in expected investment when the project moves from being entirely internally dependent to entirely externally dependent. Assuming innovative outputs are positively related to investment, we then have the following hypothesis:

H1: For US companies during the financial crisis, dependence on external finance will not change significantly the innovative output from project classes.

We next investigate the effect of asset intangibility on innovation during the crisis. Intangible assets N are assumed to rise with the level of investment, other things being equal, so $dN/dI > 0$. We also assume that innovative outputs P, being a subset of intangible assets, increase when they do, so $dP/dN > 0$.

From equation (4.1), we have the lower and upper limits on the region over which non-investment occurs. Since $d\Sigma/dT < 0$, the upper limit $\Sigma - \mu$ reduces with tangible assets T, while the lower limit $-\mu$ is unchanged and so the probability of investment rises. Hence the expected investment rises as well and $dI/dT > 0$.

The intangibility ratio of a company is the value of intangible assets divided by the value of total assets, or $N/(T+N)$. It can measure how much protection an investor has in the event of a company being wound up, and has been as a performance determinant in financial crises (Kroszner et al, 2007). The response of innovative outputs to changes in the intangibility ratio is given by $\frac{dP}{d(N/(T+N))}$. We analyse the properties of this quantity. When the derivative is non-zero, the inverse function theorem says that $\frac{dP}{d(N/(T+N))} = \left(\frac{d(N/(T+N))}{dP}\right)^{-1}$. The derivative in the bracket can be expanded using the chain rule to give

$$\frac{dP}{d(N/(T+N))} = \left(\frac{dN}{dP}\frac{dI}{dN}\frac{d(N/(T+N))}{dI}\right)^{-1}$$

or, using the inverse function theorem again and the product rule,

$$\frac{dP}{d(N/(T+N))} = \left(\left(\frac{dP}{dN} \right)^{-1} \left(\frac{dN}{dI} \right)^{-1} \left(\frac{dN/dI}{T+N} - (dT/dI + dN/dI) \frac{N}{(T+N)^2} \right) \right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN} \frac{dN}{dI} \left((dN/dI) \left(\frac{1}{T+N} - \frac{N}{(T+N)^2} \right) - (dT/dI) \frac{N}{(T+N)^2} \right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN} \frac{dN}{dI} (T+N) \left(\frac{dN}{dI} \left(1 - \frac{N}{T+N} \right) - \left(\frac{dI}{dT} \right)^{-1} \frac{N}{T+N} \right)^{-1}$$

The terms $\frac{dP}{dN}$, $\frac{dN}{dI}$, $T+N$, $\left(1-\frac{N}{T+N}\right)$, $\frac{dI}{dT}$, and $\frac{N}{T+N}$ are all positive, so $\frac{dP}{d(N/(T+N))} > 0$ if and only

$$\frac{dN}{dI} \left(1 - \frac{N}{T+N} \right) - \left(\frac{dI}{dT} \right)^{-1} \frac{N}{T+N} > 0$$

or

$$\frac{dN}{dI} \frac{dI}{dT} > \frac{N}{T}.$$

Thus, innovative outputs grow as the intangibility ratio increases if and only if the product of growth of intangible assets as investment increases and the growth of investment as tangible assets increase is sufficiently large. In other words, growth in intangible assets is induced by tangible asset growth through investment, and for innovative output growth to be associated with a rising intangibility ratio, the intangible asset growth has to be large enough to outpace the tangible asset growth. Hence, we cannot state certainly how the intangibility ratio will affect company innovative outputs.

4.3.2 University innovation during the crisis

Many US university laboratories consider basic research as their primary objective, with much of their time spent on publishing academic research (Bozeman, 2000). Nevertheless, their work often has an applied character (Mowery et al, 2001), and some of that work gives rise to commercial innovations. The funding for such innovations may come from, among other sources, industry or government. The latter source has become more important through a series of government policy initiatives including the Bayh-Dole Act of 1980 allowing universities to commercialise federally funded innovations, the National Cooperative Research Act of 1984 and its amendment in 1993 facilitating research collaborations, and the Advanced Technology Program from 1990 and the Technology Innovation Program from 2007 providing funding for research projects that often resulted in university-private sector partnerships (Bozeman, 2000; Hall et al, 2003).

A source providing funding to a university faces information problems similar to those faced by a funder of a company. It typically has less information than the university or the funded academic about their ability to implement a project, or about the project's progress. However, commercial sources funding universities usually extract information from the recipients directly rather than through the information intermediaries commonly used in financing companies, reflecting the frequent utility to the funding source of the university knowledge generated. The direct information extraction can take the form of technical queries, consultancy, direct employment, co-authoring papers, and hiring graduates and post-doctoral researchers (Boardman and Ponomariov, 2009; Bozeman and Gaughan, 2007). The US federal and state governments generally limit the information gap by competitive tender of grants, with applications having to give detailed information on their planned technological and financial aspects (see for example, Department of Health and Human Services (2007) or National Science Foundation (2013)). The applications are subject to monitoring during their progress and the possibility of non-renewal for ongoing projects. Expert evaluation of applications is maintained by use of peer review.

The provision of funding for US university innovation is not necessarily as badly disrupted by a financial crisis as provision for company innovation. The largest university funding source is the US government which is less financially constrained than US companies during crises. It could run deficits and make available extra funds to universities, which it did in 2007-8. Available funds from commercial sources may be subject to acute pressure due to the financial crisis and recession, as described above. Given the non-market form of the informational ties between universities and capital providers, the collapse of the information provision function of the market does not affect information passing directly between them.

These observations can be given a formal mathematical form in order to theorise on how university innovation responded to the financial crisis. We analyse investment by a government investor who values the income from a project (whether it accrues to the government or the university), and also other consequences from investment. During the crisis, a government investor in a project expects to receive an immediate utility (net of investment cost) of

$$\mu + P + \varepsilon$$

where μ is the net income from investment, P is a measure of the political value of other consequences of investment in excess of any benefits before the crisis, and ε is an error term with distribution function $f(\varepsilon)$.

Investment occurs if

$$\mu + P + \varepsilon > 0$$

or

$$\varepsilon > -P - \mu .$$

A commercially motivated university manager will invest if

$$\varepsilon > -\mu .$$

Thus, the excess in investment by investors over managers during the crisis occurs in the region given by

$$-\mu \geq \varepsilon > -P - \mu \qquad (4.2)$$

This is the region in which a project that was did not have access to external finance would not be given approval, while the same project that was externally financed would result in investment.

Prior to the crisis, the additional political benefits of investment in the crisis are not present, so $P = 0$. They receive an immediate net utility from investment of

$$\mu_b + \varepsilon$$

where μ_b is the net income from investment before the crisis. Since there is a recession at the same time as the financial crisis, $\mu_b > \mu$. Investment occurs if

$$\varepsilon > -\mu_b .$$

Investment occurs during the crisis but not before it if

$$-\mu_b \geq \varepsilon > -P - \mu ,$$

conditional on the political benefits being sufficiently large so that $P > \mu_b - \mu$. The error term lies in the region with probability $\int_{-P-\mu}^{-\mu_b} f(\varepsilon)d\varepsilon$. In section 4.2, we saw that there was a reasonably large increase in observed government funding to R&D investment during the crisis relative to investment before it, so the probability is quite large.

From equation (4.2), the probability that a investor would fund a project but a manager would not is $\int_{-P-\mu}^{-\mu} f(\varepsilon)d\varepsilon$. Since $\mu_b > \mu$, it follows that

$$\int_{-P-\mu}^{-\mu} f(\varepsilon)d\varepsilon > \int_{-P-\mu}^{-\mu_b} f(\varepsilon)d\varepsilon > 0$$

and so there is a quite large probability that a project would be financed if external finance is necessary but not financed if internal finance is the source. It follows that there is a quite large change in expected investment when the project moves from being entirely internally dependent to entirely externally dependent. Assuming innovative outputs are positively related to investment, we then have the following hypothesis:

H2: For US universities during the financial crisis, dependence on external finance will increase the innovative output of project classes.

The effect of the intangibility ratio on university innovation during the crisis is analysed in a similar way as for company innovation. We again assume intangible assets *N* rise with the level of investment so $dN/dI > 0$, and innovative outputs *P* increase with intangible assets, so $dP/dN > 0$. The limits on the region in which investors invest more than managers in equation (4.2) are both independent of tangible assets *T*, so investment *I* during the crisis is independent of *T*, and $dT/dI = 0$.

The derivative of innovative outputs with respect to the intangibility ratio can be expanded as before to

$$\frac{dP}{d(N/(T+N))} = \left(\frac{dN}{dP}\frac{dI}{dN}\frac{d(N/(T+N))}{dI}\right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN}\frac{dN}{dI}(T+N)\left(\frac{dN}{dI}\left(1-\frac{N}{T+N}\right)-\frac{dT}{dI}\frac{N}{T+N}\right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN}\frac{dN}{dI}(T+N)\left(\frac{dN}{dI}\left(1-\frac{N}{T+N}\right)\right)^{-1}$$

since $dT/dI = 0$. The terms $\frac{dP}{dN}$, $\frac{dN}{dI}$, $T+N$, and $\left(1-\frac{N}{T+N}\right)$ are all positive, so $\frac{dP}{d(N/(T+N))} > 0$.

So, university innovative outputs grow as the intangibility ratio rises. We therefore have the following hypothesis:

H3: For US universities during the financial crisis, higher intangibility ratios will increase the innovative output of project classes.

4.3.3 Control variables

The main variables for testing our hypotheses will be external financial dependence and the asset intangibility ratio, whose construction we will describe in section 4.4. We also include several control variables in the analysis. Together with lagged innovative outputs, they are used to capture other influences on the change in innovation during the crisis, including the effect of demand shifts due to the associated recession. In this subsection, we present the expected effect of the control variables on innovation.

The novelty of the type of innovated product

The financial crisis may have been associated with either of two Schumpeterian hypotheses, namely creative accumulation or creative destruction (Archibugi et al 2013a). Under the creative accumulation hypothesis, innovations are incremental and due to established innovators. They are the innovators who persist during the crisis, and we may expect them to build on their existing work with more established products. Thus, the age of the product type could be positively associated with changes in the volume of innovation. Under the creative destruction hypothesis, innovations are radical and occur in new areas. The financial crisis created instability and weakened the position of existing innovators. The crisis would be a time of new product type introduction, so that the age of the product type could be negatively associated with change in the amount of innovation. We do not take a prior position on which hypothesis best describes innovation during the crisis, and leave the data to determine the result.

R&D intensity

R&D intensity is measured as R&D divided by sales. Between 2008 and 2009, R&D funding for companies reduced (National Science Board (2012), appendix table 4-3). As a result, they had lower funds for sustaining research in previously initiated projects and for bringing partially finished projects to completion. The difficulties may have been most acute for expensive and risky R&D intensive projects. Thus, during the financial crisis we may expect bigger declines in commercial innovation for companies undertaking more R&D intensive projects. Universities had increased R&D funding indicating that the effect of R&D

intensity would increase, but the impact would be moderated by their primary non-commercial objectives.

Capital to labour ratio

Large investments are made in R&D in the US (see section 4.2.1), and single successful innovative products can be very costly (see DiMasi et al (2003), Adams and Brantner (2006), and DiMasi and Grabowski (2007) for the costs of pharmaceuticals). Human skill and ingenuity is important in the innovation process, and employee remunerations are a large cost in it. For example, in 2008 the total wage bill for US corporate R&D workers was around $114 billion[1] compared with total business R&D investment of $291 billion (see section 4.2.1). We do not have any strong prior expectations of whether a high capital to labour ratio for a production process will be associated with higher or lower innovation rates. During the financial crisis, capital was rationed and innovation projects dependent on capital may have been hindered more than those with greater dependence on labour. Innovative output from such projects may have declined. However, as we do not expect a strong initial relation between innovation and the capital to labour ratio, the decline may be weak. Kroszner et al (2007) finds the capital to labour ratio has an insignificant effect on industrial value added growth changes between financial crisis periods and the periods preceding them.

4.4 Data

4.4.1 Preparation

In this section, we present the data used in our empirical testing[2]. It comes from two sources, the US Patent and Trademark Office (USPTO) online patent database and Compustat financial data. The cross-sectional unit of analysis is patent class, a USPTO classification of inventions according to technological type. There are 473 such classes, given directly in the USPTO data. For the Compustat financial data, we aggregate the data by

[1] National Science Board (2012), table 3-7 puts average annual salaries for science and engineering workers at $80,170 in 2010. Table 3-13 gives total company R&D workers at 1,424,000 in 2008. We multiply to give a total wage bill of $114 billion.
[2] The data and STATA code used in estimation are available from the author on request.

industry code and then use the code to map into patent class. The patent class thus serves as a means of identifying technological and financial characteristics of innovation undertaken by US companies and US universities. By construction, the quantities derived from the Compustat data (external dependence, intangibility, R&D intensity, and the capital to labour ratio) allow for the industrial composition of their patent class.

USPTO data

The USPTO online patent database contains details of patent applications in the US unless the applicant has explicitly requested privacy prior to grant. Patent applications are published eighteen months after the applicant files for a patent. The database records applicant name, country of residence of the organisation or person to whom the application is issued, the application date, and the patent class of the invention. We accessed the data in March 2014.

Compustat data

We use data from all companies on Compustat for constructing our financial measures. Rajan and Zingales (1998) and Kroszner et al (2007) also use the full set of Compustat companies in preparing measures of external dependence, which results in the statistics reflecting the finances of US publicly quoted and larger companies. Our measures are all ratios of financial quantities, and are used for companies and universities operating commercially by undertaking patenting. Conceivably the relevant ratios of financial quantities in commercial operations run by US universities may be different from those in US companies. If true, then our hypothesis testing remains valid if the adjustment factor between the financial ratios of companies and university commercial operations is constant across different innovation projects. Moreover, we run separate estimates for companies and universities, so there are no interpretational ambiguities for a combined coefficient.

Our statistics for Compustat data are grouped by two digit Standard Industrial Classification (SIC) System codes. As our cross-sectional unit for estimation is the USPTO patent class, we map from SIC based statistics to patent class based statistics using the concordance file between the two classifications provided by USPTO (2008b). The mapping to patent class is not unique as there are multiple subclasses which may be allocated different SIC codes, so we calculate average statistics over subclasses. For every patent class, the percentage of each SIC code corresponding to the class is calculated. The statistics for the patent class are derived as the sum of the percentage weighted statistics for the individual SIC codes. The formulas take the form

$$S_C = \sum_i \frac{n_{C,i}}{\sum_j n_{C,j}} S_i$$

where S_C is the statistic for patent class C, S_i is the statistic for SIC code i, $n_{C,i}$ is the number of subclasses in class C corresponding to SIC code i, and the summations run over all SIC codes.

As a means of determining the financial conditions under which an innovation was produced, the mapping is inevitably inexact. The difficulty arises from the allocation of patents to specific industries, as noted by Jaffe and Palmer (1997) in their matching of patents to industrial environmental cost data. An invention may have been produced by an innovator whose core operation is not in the SIC code allocated to the invention. So the invention may have been produced in financial conditions that differ from those that apply to companies producing under the allocated SIC code. We assume that any mismatches occur as random noise in the data and do not distort our results.

Our statistics S_i derived from Compustat data (external dependence, intangibility, R&D intensity, and the capital to labour ratio) all take the form of ratios and depend on the SIC code i. To calculate them, we first calculate the corresponding statistics $S_{i,j}$ for each SIC code and company code j. They are calculated as ten year averages over 2000-9, with for example the intangibility ratio given by

$$S_{i,j} = \frac{\sum_{k=2000}^{2009} \nu_{i,j,k}}{\sum_{k=2000}^{2009} \tau_{i,j,k} + \nu_{i,j,k}}$$

where $\nu_{i,j,k}$ are the total intangible assets for company coded j in year k operating in industry i, and $\tau_{i,j,k}$ are the total tangible assets over the same period. The statistic S_i for the SIC code are then the median of $S_{i,j}$ over all companies.

Variables

Patent counts

We use counts of patent applications as our measure of innovation within each patent class and split by innovator type, using USPTO data. Patents have long been used as such a measure (Scherer 1965, Schmookler 1962), and their advantages and disadvantages extensively discussed (Archibugi and Pianta, 1996; Basberg, 1987; Hagedoorn and Cloodt, 2003). The extent to which patents measure innovation may differ by innovator type. Universities may have a lower proclivity to patent their innovation than companies because of their largely different objectives (Bozeman, 2000). We may nevertheless infer that a contraction due to the crisis in the number of innovations, and in particular in the number of innovations produced with a commercial orientation, will generally be associated with a reduction in the number of patents for any innovator type.

We collect monthly data for the period from January 2006 to December 2009, giving 348,000 patents in total. There is an 18 month delay between filing and publication of applications, but as our data was collected in March 2014 the delay does not affect included applications. Applications that are made with a request of privacy, and are due to be successfully granted, and take more than four years to process may not be included in the data (with potentially greater effect on patent counts in later months). However, we expect the numbers to be small because the mean delay between patent application and issue or abandonment was 32 months in 2008 (USPTO (2008a), workload table 4) so that the large majority of applications would have been handled four years after they were made. Moreover, any omissions will not change the comparative results across innovators.

There is no single US country code to allow us to identify all US applicants on the USPTO database, but it does record the US state in which an American applicant is resident. We sum the patent counts for each state to obtain a patent counts for the whole US. The academic origin of applicants is not recorded on the USPTO database. We separate academic and non-academic applicants by searches on the applicant name. A representative subset of academic applicants is identified by searching the name for the words "university", "college", "school", or "institute of technology". These search terms identify most of the primary institutional names for academic applicants, including the largest patenters[3]. Some academic institutions may patent under secondary names omitting these terms, and these patents will be included in our non-academic counts. As the number of company patents far exceeds university patents, the contamination of company patent counts will be very limited.

External dependence

External dependence is calculated as the ratio of capital expenditures not financed by net operating cash flow to capital expenditure. The Compustat code for capital expenditures is *capx*, and for net operating cash flow is *oancf*, so the formula for external dependence is $(capx - oancf)/capx$. The list of external dependence values by patent class is available at our website in .csv format[4].

3 http://www.uspto.gov/web/offices/ac/ido/oeip/taf/univ/total_counts/univ_ct_list_2012.htm

4 http://ebasic.easily.co.uk/02E044/05304E/Ext_dep_by_patent_class.csv

Intangibility

Intangibility is the ratio of intangible assets to total assets. The Compustat code for intangible assets is *intan*, and for total assets is *at*.

The novelty of the innovated product class

The novelty of the innovated product type is measured by the date at which the USPTO introduced the corresponding patent class. The earliest establishment date is 1899 for patent classes including wood turning products and envelopes. The latest introduction date is 2007 for combinatorial chemistry technology.

The USPTO class introduction date is likely to measure the novelty of a type of innovated product only with a delay. It may not be immediately clear that the early patents in the product type represent a major departure from existing product types, and their citations will necessarily locate them within existing classes. The USPTO may only wish to introduce a new class only when a sufficient number of relevant patents is reached, and the identification and decision processes will not be immediate. Our econometric method will absorb into the constant term the average delay between the date at which a product type was first innovated and the date at which the corresponding USPTO class was introduced[5].

R&D intensity

R&D intensity is calculated as the ratio of R&D to sales. The respective Compustat codes are *xrd* and *sale*.

Capital to labour ratio

The capital to labour ratio is calculated as fixed assets divided by number of employees. The Compustat code for fixed assets is *ppent*, and for employees is *emp*.

[5] Thanks to Pia Weiss for pointing out the likely difference between innovation date and patent class introduction date, and suggesting reasons for it.

Time

Time is measured in months since April 2001 (the first month of data availability), with April 2001 = 1.

4.4.2 Summary statistics

In table 4.1 we see summary statistics for the financial and other characteristics of the innovation undertaken by each innovator type. The mean external dependence of company innovation is lower than university innovation. For the classes in which companies innovate, internally generated funds are around 164 percent of total capital expenditures in US commercial conditions, while for universities the amount is 124 percent. The mean level of asset intangibility in those classes is similar for both innovator types at 14 and 15 percent. The mean establishment dates of the patent classes in which they operate is also similar, in the second half of the 1970s. Both innovate in the oldest and newest classes. The R&D intensity is higher in classes in which companies innovate compared with those in which universities innovate. The capital to labour ratio is lower for the projects of companies than those of universities.

Table 4.1

Summary statistics for innovation portfolios of each innovator type

	US companies			US universities		
	Mean	Min	Max	Mean	Min	Max
External dependence	-0.64	-5.55	0.84	-0.24	-5.49	0.84
Intangibility	0.14	0	0.66	0.15	0	0.66
Date established	1975	1899	2007	1978	1899	2007
R&D intensity	0.0029	0	0.0866	0.0017	0	0.0865
Capital/labour	115.3	0	2783.3	173.3	0	2783.3

Notes: mean values are weighted by patent counts.

4.4.3 Changes in aggregate patent counts during the crisis

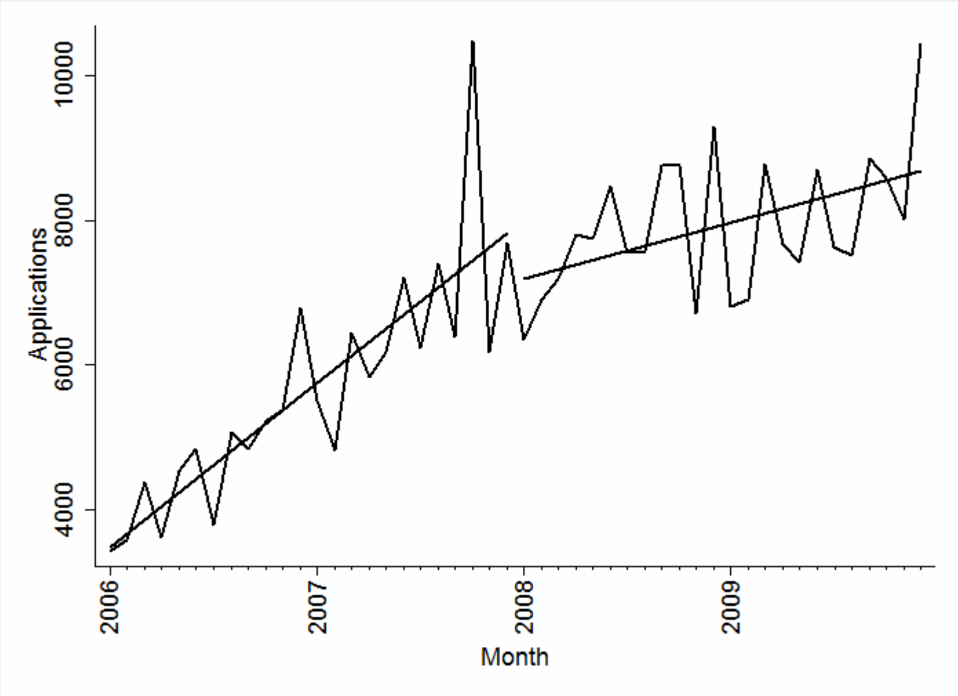

Figure 4.1. Aggregate patent counts by US companies with OLS lines fitted for 2006-7 and 2008-9.

Figure 4.1 shows aggregate patent counts by US companies. There are 326,000 patents in total over the period 2006-9, and the aggregate patenting appears to slow down around the end of 2007. To demonstrate the change in broad terms, the patent counts from the period 2006-7 are regressed on a time trend by OLS, and then the same is done for the period 2008-9. The two fitted lines are superimposed on the graph. The change in level and trend between the two periods is clear. Figure 4.2 shows aggregate patent counts for US universities; there are 22,000 patents over the whole period. Their patenting seems to change after the start of the financial crisis, in both level and trend.

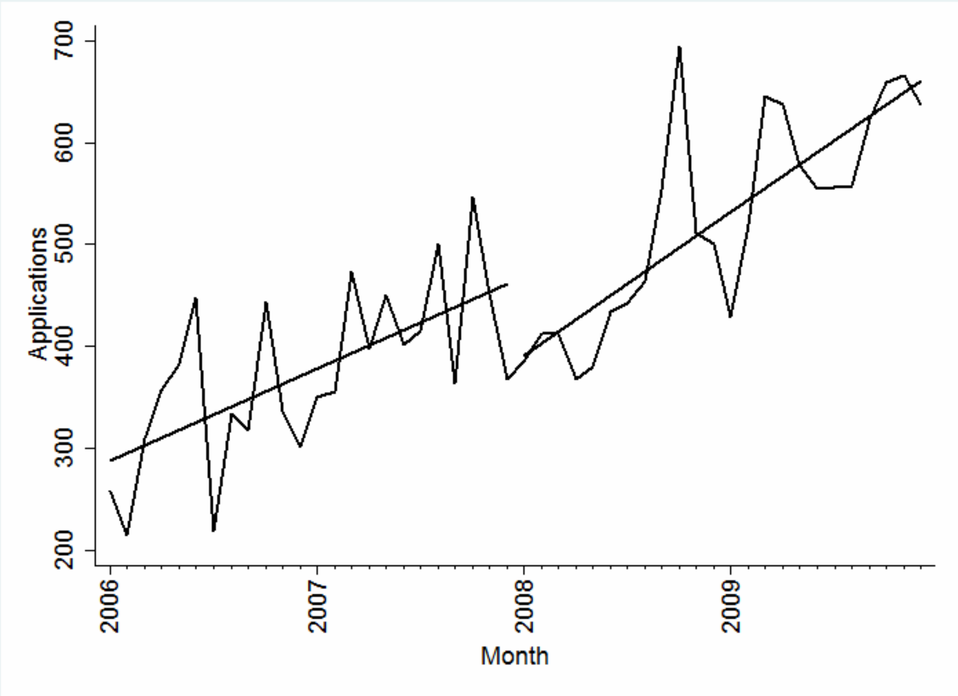

Figure 4.2. Aggregate patent counts by US universities with OLS lines fitted for 2006-7 and 2008-9.

To examine whether the change in aggregate patent rates for US companies is significant, we ran F tests for the constant and trend coefficient in the pre-break and post-break periods being jointly equal, allowing for possible break dates between January 2007 and December 2009. Figure 4.3 shows the p-values against break dates. The p-values are low throughout the period, indicating a significant structural change. The most likely break date is at the end of 2007, giving us confidence to take December 2007 as a change date in the subsequent analysis.

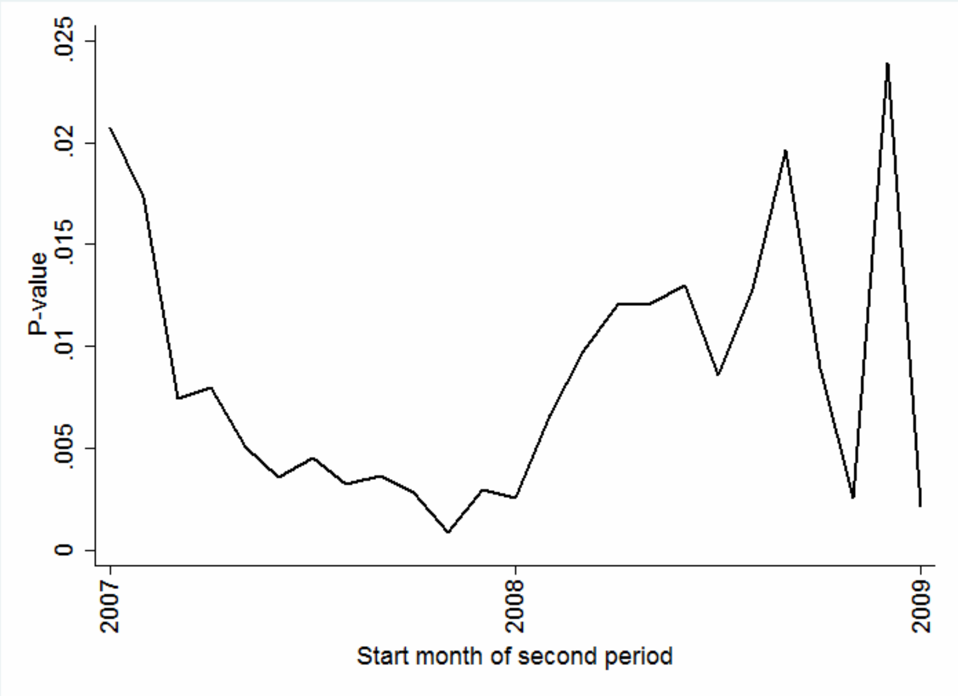

Figure 4.3. P-values against break dates for an F-test of OLS parameter change between (January 2006, break date) and (break date, December 2009). US company data is used.

To demonstrate the changes for patent classes around the financial crisis, we ran negative binomial estimations for patent counts in each class in the periods 2006-7 and 2008-9, with the logarithm of the expected value linearly dependent on time (this procedure forms part of the estimation method we describe for our full analysis in section 4.5). Predicted patent counts in January 2008 were calculated from the estimation results for both periods, giving us a set of predicted patents for the 2006-7 estimates and a set for the 2008-9 estimates. Figure 4.4 plots the predicted patents from the US company data as kernel densities. The solid line shows the predictions from the 2006-7 estimates, and the dashed line shows the predictions from the 2008-9 estimates. The 2008-9 density is a compression towards zero of the 2006-7 density, representing a general reduction in patenting.

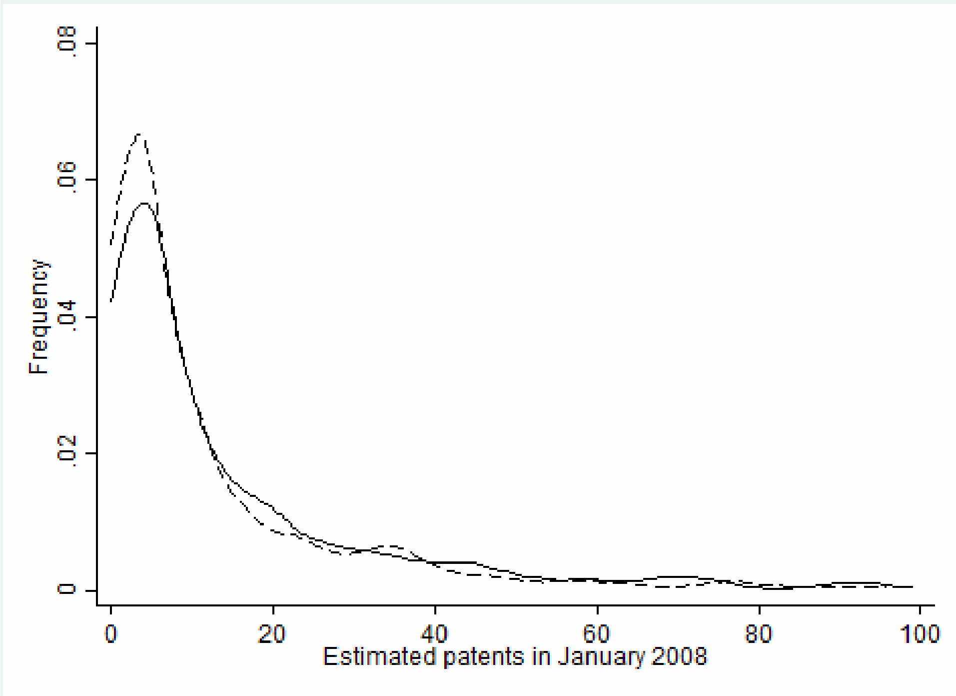

Figure 4.4. Kernel density of estimated patents in January 2008 across patent classes. *Notes*: the solid line is for estimates from 2006-7 and the dashed line is for estimates from 2008-9. US company data is used.

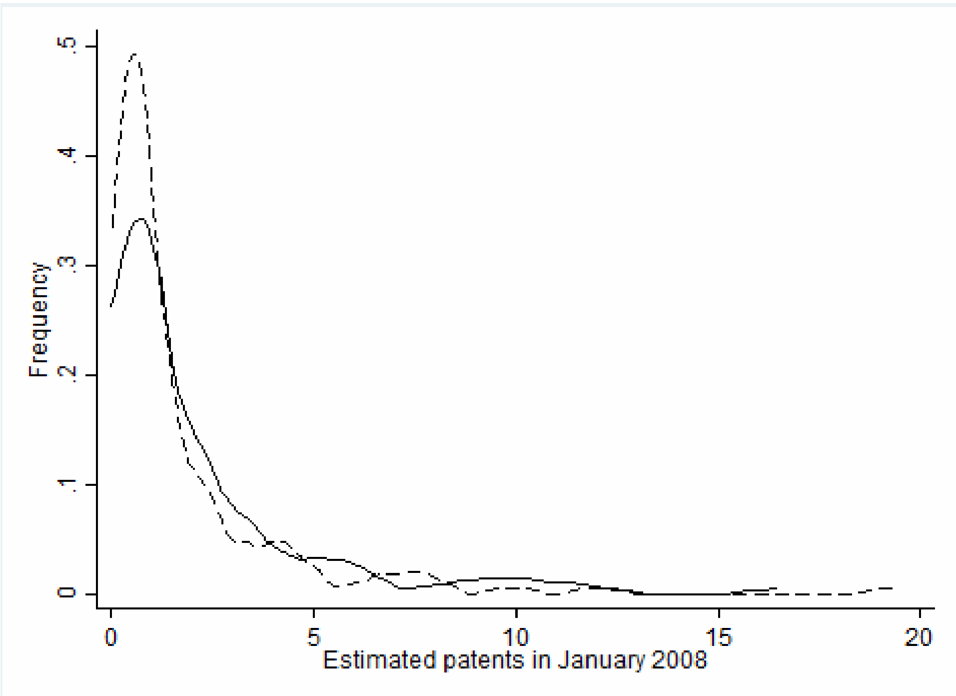

Figure 4.5. Kernel density of estimated patents in January 2008 across patent classes. *Notes*: the solid line is for estimates from 2006-7 and the dashed line is for estimates from 2008-9. US university data is used.

In figure 4.5, we see the corresponding densities for US universities. The number of patent classes predicted to have just a single patent increases in the 2008-9 estimates, and there is again a broad compression towards zero, indicating a reduction in patenting.

4.5. Empirical method

In this section we present our testing and estimation method. We assume a multiplicative model for predicted patent counts conditional on the information available during the crisis, relating it to the predicted patent counts prior to the crisis and an adjustment factor influencing the relation between the two. The adjustment factor is exponential and guarantees positive patent counts, as is standard in the empirical literature (Cameron and Trivedi, 1998). The functional form is

$$p_{i,t} \mid I^{+} = \alpha \ (p_{i,t} \mid I^{-})^{\beta} \ \ \exp(\gamma + \Gamma' X_i + u_i) \qquad (4.3)$$

where $p_{i,t} \mid I$ are predicted patent counts in patent class *i* at time *t* and conditional on information set *I*, I^{+} is the information available during the crisis, I^{-} is the information available before the crisis, α, β and γ are constants with $\alpha > 0$, X_{i} is a vector of time-invariant patent class characteristics, Γ is a vector constant with the same dimension as X_{i}, and u_{i} is a zero mean normal error.

Hypotheses H1 and H2 examine how external dependence affects the change in innovation during the crisis for different innovator types. Equation (4.3) may be written as

$$(p_{i,t} \mid I^{+}) / (p_{i,t} \mid I^{-}) = \alpha \ (p_{i,t} \mid I^{-})^{\beta - 1} \ \ \exp(\gamma + \Gamma' X_i + u_i)$$

The left hand side of the equation is the ratio of patents predicted during the crisis to those predicted before the crisis, and so measures innovation change. We test hypothesis H1 by looking at the significance of external dependence on the right hand side of the equation when company data is used, and hypothesis H2 by looking at the sign and significance of external dependence when university data is used. Hypothesis H3 examines how intangibility ratios affect innovation, and we test it by looking at the sign and significance of the intangibility ratio on the right hand side of the equation when university data is used.

Taking logs of equation (4.3) we have

$$\ln(p_{i,t} \mid I^{-}) = \ln\alpha + \beta\ln(p_{i,t} \mid I^{+}) + \gamma + \Gamma' X_i + u_i \,. \qquad (4.4)$$

This specification for examining the crisis' effect is similar to that used in Archibugi et al (2013a), where the change in innovation between two years is measured. We could bring our specification even closer to their model by comparing changes in patents in successive time periods, t and $t + 1$. However, we prefer to examine an instant effect, rather than a delayed one. The reason is that any crisis effect may tend to correct itself over time especially in patent classes where it has been severe, so that an estimation using successive periods may not capture the full crisis effect. Moreover, we prefer to use extended evidence of patenting behaviour to estimate mean patenting rates rather than patent rates in one period, in order to reduce measurement volatility. As a prediction method for calculating $p_{i,t} \mid I^{+}$ and $p_{i,t} \mid I^{-}$, we could use averages or sums over successive periods (for example, to give annual rates of innovation, as in Archibugi et al (2013a)), which would be acceptable in the absence of trends in the data. However, trends in patenting in each class are likely. So we use an equivalent method to averaging, but one which allows for trends. We calculate the predicted patents $p_{i,t} \mid I^{+}$ and $p_{i,t} \mid I^{-}$ in class i at time t by running two sets of negative binomial regressions for counts in each patent class:

$$\log(P_{i,t}) = \varphi_i + \psi_i \, t \,, \qquad (4.5)$$

$P_{\mathrm{i,t}}$ ~ negative binomial,

where $P_{i,t}$ are patent counts in class i at time t, and φ_i and ψ_i are class specific constants. Patenting in each class may be generated by distinct processes and be at different life stages, and so we make no assumptions about the commonality of parameters across classes in generating predictions.

The estimation is performed first over the 24 month period from January 2006 to December 2007, which we call the pre-crisis period, and then over the period from January 2008 to December 2009, which we term the crisis period. We exclude any patent classes in which the number of patents is ten or less over the whole 2006 to 2009 period. Once we have the regression coefficients, we take $p_{i,t} \mid I^-$ to be the predicted value at time t from the early period equation, and $p_{i,t} \mid I^+$ to be the predicted value from the late period equation.

We estimate equation (4.4) using OLS across classes i with robust standard errors, with the predicted patents evaluated in January 2008. The influence of extreme patent class values is eliminated by excluding any classes in which the predicted January 2008 patent counts from either the 2006-7 or 2008-9 periods exceed 100 for US companies, and 20 for US universities. The exclusion is of less than the top seven percent of values for each innovator type.

We also estimate a modified version of equation (4.4) using cumulative patents over a time period T,

$$\ln \sum_{t \in T} p_{i,t} \mid I^- = \ln \alpha + \beta \ln \sum_{i \in T} p_{i,t} \mid I^+ + \gamma + \Gamma' X_i + u_i . \qquad (4.6)$$

The values for cumulative predicted patents are produced by predicting two sets of cumulative patents over the period T, using estimates from equation (4.5) based on the data from 2006-7 to predict $\sum_{t \in T} p_{i,t} \mid I^-$ and from 2008-9 to predict $\sum_{t \in T} p_{i,t} \mid I^{+}$. In the OLS estimation of equation (4.6), we exclude classes with early estimated or late estimated cumulative patents exceeding 5000 for companies, and 500 for universities. Less than the top five percent of values are excluded for each innovator type.

4.6 Results

4.6.1 Immediate and cumulative effects of the financial crisis

In this section we present our results, starting with the crisis' immediate and cumulative effects on innovation in table 4.2. The first two columns present regression results where the determined variable is the logarithm of the patent count in January 2008 as predicted using data from 2008-9. In column one, we see the results for US companies. External dependence has an insignificant effect on the count, consistent with hypothesis one was that there would be no significant link between the two. Column two gives coefficients for US universities. External dependence is significantly associated with increased patenting during the crisis, consistent with hypothesis two, while intangibility is significantly associated with increased patenting during the crisis, as anticipated in hypothesis three.

Columns three and four look at regressions with the logarithm of cumulative predicted patents as determined variable. Column three has results for companies. External dependence has a significant positive effect on the cumulative patenting over 2008-9, indicating that the effect in January 2008 becomes more positive over time. Column four presents results for universities, with a significant positive links between cumulative patenting and both external dependence and intangibility. The same links are observed in January 2008.

Table 4.2

Determinants of the logs of the predicted patent count at the start of the crisis and the sum of the predicted patent counts during the crisis

Dependent variable:	Log late predicted patents in January 2008		Log late predicted patents cumulated over 2008-9	
	US companies	US universities	US companies	US universities
	OLS regressions			
	(1)	(2)	(3)	(4)
External dependence	0.0254	0.1990*	0.0858**	0.2439**
	0.0306	0.1012	0.0415	0.103
Intangibility	-0.0857	1.1103**	0.305	1.0084**
	0.2238	0.4257	0.3645	0.4088
Log early predicted patents	0.9497***	0.6994***	0.7663***	0.4038***
	0.0329	0.0617	0.036	0.0505
Establishment date	-0.0008	-0.0057**	0.0011	0.0018
	0.0009	0.0025	0.0014	0.003
R&D intensity	-2.9369	-7.8922*	-5.2830*	-9.7988*
	2.1868	4.7325	2.8048	5.6922
Capital to labour ratio	-0.0002**	-0.0006**	-0.0002*	0.0001
	0.0001	0.0003	0.0001	0.0002
Constant	1.488	11.0805**	-1.225	-1.6421
	1.7817	4.9167	2.646	6.0256
R^2	0.87	0.62	0.77	0.46
Observations	369	140	372	134

Notes: Robust standard errors are shown below the coefficients.

*   Ten percent significance.

**   Five percent significance.

***   One percent significance.

4.6.2 Results split by age of patent class

Table 4.3 presents estimations split by the age of the patent class, with new patent classes established after 1990 and old patent classes established before 1991. This division gives a reasonable approximation for the split between high technology and other technology. The results for new classes are shown in columns one and two. Coefficient estimates for US companies are presented in column one, where external dependence is insignificantly associated with patenting. The results for US universities are in column two, where neither external dependence nor intangibility is associated with patenting. The small sample size will have influenced the low coefficient significance.

Table 4.3

Determinants of the logs of the predicted patent count in January 2008, by patent class age

	Dependent variable: log late predicted patents in January 2008			
	New classes		Old classes	
	US companies	US universities	US companies	US universities
	OLS regressions			
	(1)	(2)	(3)	(4)
External dependence	-0.0428	0.0186	0.0224	0.2162*
	0.118	0.3345	0.0313	0.1102
Intangibility	0.1676	0.7474	-0.2079	1.1014**
	0.9583	1.3296	0.2272	0.468
Log early predicted patents	1.1308***	0.6025***	0.9223***	0.7856***
	0.072	0.1117	0.0364	0.0767
Establishment date	-0.0065	0.0296	-0.0002	-0.0078**
	0.0233	0.0342	0.001	0.0036
R&D intensity	4.0078	-17.9753	-2.8549	-6.7787
	4.2495	10.7814	2.3566	4.7261
Capital to labour ratio	-0.0001	-0.0009***	-0.0001	-0.0003
	0.0001	0.0002	0.0001	0.0002
Constant	12.2738	-59.3178	0.4251	15.1319**
	46.257	68.3041	1.9659	6.9697
R^2	0.92	0.6	0.86	0.67
Observations	61	43	308	97

Notes: Robust standard errors are shown below the coefficients.

* Ten percent significance.

** Five percent significance.

*** One percent significance.

Columns three and four give estimates for data based on old patent classes. Column three shows that for US companies there was no significant association between external dependence and patenting. A significant positive relation is shown for US universities in column four. The association is also significant and positive between external dependence and patenting. Hypotheses one, two, and three all hold for patenting in old classes.

4.6.3 Estimates based on OLS predictions of patenting

In calculating the results in section 4.6.1, the predicted patent counts are derived from negative binomial estimation within each patent class, so they grow exponentially over time. In this section, we calculate results in which the predictions are derived from OLS estimations in each class, with linear growth in patenting over time. The extra caution comes at the cost of allowing negative patenting in classes and of a discrete non-symmetric random variable being approximated by a normal variable; however, as section 4.7 will show, the aggregate OLS behaviour predicts actual patenting after the crisis more closely than aggregate negative binomial predictions.

We continue to estimate results from our main cross sectional regressions given by equations (4.4) and (4.6). However for predicting patents within classes we replace the negative binomial equation (4.5) with an OLS equation

$$P_{i,t} = \varphi_i + \psi_i \; t + v_{i,t} \, ,$$

where φ_i and ψ_i are class specific constants and $v_{i,t}$ is a zero mean normal variable. The estimation is performed over the period from January 2006 to December 2007, then over January 2008 to December 2009. We again exclude any patent classes in which the number of patents is ten or less over the whole 2006 to 2009 period. Once we have the regression coefficients, we use predictions from the early period and late period estimations as variables in our main regressions.

Table 4.4 contains our results, with the first two columns presenting coefficient estimates when the dependent variable is the logarithm of predicted January 2008 patents. In column one, US company data is used and external dependence is found to have an insignificant association with patenting, as expected from hypothesis one. Column two shows that for US universities there is a significant positive relation between external dependence and patenting, consistent with hypothesis two. The relation between intangibility and the patent count is significant and positive, as hypothesis three anticipated. Overall, the evidence provided for hypotheses 1, 2, and 3 is strong here as in the main table 4.2.

Table 4.4

Determinants of the logs of the predicted patent count at the start of the crisis and the sum of the predicted patent counts during the crisis; prediction by OLS

Dependent variable:	Log late predicted patents in January 2008		Log late predicted patents cumulated over 2008-9	
	US companies	US universities	US companies	US universities
	OLS regressions			
	(1)	(2)	(3)	(4)
External dependence	0.0329	0.2534**	0.0689**	0.2781***
	0.0319	0.1001	0.0289	0.0667
Intangibility	-0.1108	1.1115**	0.3049	0.8959***
	0.2471	0.4496	0.2076	0.3237
Log early predicted patents	0.9447***	0.8276***	0.8857***	0.6662***
	0.0394	0.0446	0.0393	0.0567
Establishment date	-0.0006	-0.0042*	-0.0002	-0.0026
	0.001	0.0024	0.001	0.0022
R&D intensity	-4.1775	-7.2524	-3.5887	-9.0298***
	2.8012	4.5322	2.188	3.2574
Capital to labour ratio	-0.0001*	-0.0005***	-0.0002***	-0.0003**
	0.0001	0.0001	0.0001	0.0002
Constant	1.3011	8.1784*	0.8929	6.4551
	1.9036	4.6957	1.8581	4.31
R^2	0.88	0.74	0.89	0.68
Observations	386	134	373	129

Notes: Robust standard errors are shown below the coefficients.

* Ten percent significance.

** Five percent significance.

*** One percent significance.

Columns three and four report estimates where the dependent variable is the logarithm of patents cumulated over 2008-9. In column three we see that for companies there is a positive relation between external dependence and cumulative patenting. Column four employs university data, and shows that there is a significant positive association between cumulative patenting and both external dependence and intangibility. As a whole, the findings are similar to those in table 4.2 where negative binomial projections are used.

7. Counterfactuals

The growth of unregulated debts among financial institutions has been presented as a major contributing factor to the 2007-8 crisis (Brunnermeier, 2009; Calomiris, 2008), and market-based solutions have been advanced to alter and constrain the behaviour of financial institutions (Acharya et al, 2009). They offer the possibility of insulating the financial and real economies from systemic build up of risk, such as that emerging from the sub-prime mortgage market. More stringent measures would reduce the role of the financial markets in funding companies, but the direction of international travel has been towards increased market based development. A movement towards a more commercial approach has been seen in US universities as well, for regulatory, technological, administrative, and financial reasons (Mowery et al, 2001).

In this section, we investigate the effect of alternative responses to portfolio characteristics on innovation during the crisis. In our first counterfactual companies continue to work on the same projects as before, and the patenting in January 2008 and over 2008-9 is calculated as if they were experiencing the same output response to those projects as universities. Our second counterfactual examines outcomes when universities adopt the response of companies. Calculations are performed based on the parameters estimated in table 4.2.

The statistics we examine are expected late predictions calculated from equations (4.4) and (4.6), minus the early predictions, and summed across all patent classes:

$$\sum_i (E(\overline{p_{i,t} \mid I^+}) - p_{i,t} \mid I^-)$$

and

$$\sum_i (E(\overline{\sum_{t \in T} p_{i,t} \mid I^+}) - \sum_{t \in T} p_{i,t} \mid I^-)$$

where E denotes the expectations operator, $\overline{Y}$ denotes the fitted value of Y, and the other notation is as for equations (4.3) and (4.6). The expected predicted patents counts are calculated as

$$E(\overline{p_{i,t} \mid I^+}) = \alpha \ (p_{i,t} \mid I^-)^{\beta} \ \exp(\gamma + \Gamma' X_i) E(\exp(u_t))$$

and

$$E(\overline{\sum_{t \in T} p_{i,t} \mid I^+}) = \alpha \ (\sum_{t \in T} p_{i,t} \mid I^-)^{\beta} \ \exp(\gamma + \Gamma' X_i) E(\exp(u_t))$$

where the additional notation is as below equation (4.3). The exponential error term is calculated as

$$E(\exp(u_t)) = \exp(0.5\sigma^2)$$

where σ is the root mean squared error from the estimations in table 4.2. For the counterfactuals, we replace one or more of the coefficients and exponentiated error term from the estimated equation with the coefficients and error from the alternative equation. In the summations, we do not sum over elements with extreme predicted values, using the same definitions of extreme values as in section 4.5.

Table 4.5

Patenting change during the crisis on switching to a different institution's response parameters while maintaining the original institution's innovation portfolio

Estimation method	Negative binomial		OLS	
From parameters and innovation portfolio of	US companies	US universities	US companies	US universities
To parameters of	US universities	US companies	US universities	US companies
In January 2008				
Expected patent crisis change before adjustment	-558	-54	-262	-34
Expected change after all adjustment	-2890	-6	-2,359	22
Cumulative over 2008-9				
Expected patent crisis change before adjustment	-110,912	-11,455	-46,367	-2,419
Expected change after all adjustment	-194,716	-5,589	-95,092	-1,337

Table 4.5 presents our results, with the top panel showing patenting in January 2008 and the bottom panel showing cumulative patenting over 2008-9. Columns one and two use negative binomial predictions, while columns three and four use OLS predictions. In column one we see the consequences of the crisis response to the characteristics of US company innovation becoming like that experienced by US universities. The top panel shows the immediate effect. There is a substantial impact on patenting in January 2008, with 2,300 fewer patent applications. In the low panel, the cumulative effect of the change is shown. The decline in US company patenting goes from 111,000 applications to 195,000 applications, representing an additional loss of innovation outputs of 84,000 applications.

In the counterfactual in column two, US universities are fully integrated in the market and their patenting changes as if they were US companies during the crisis. From the top panel, it can be seen that adopting the alternative responses is associated with an increase in patenting of 48 applications. The lower panel shows that the cumulative effect over 2008-9 of adopting the alternative responses is large relative to base patenting; the decline in innovation goes from 11,500 applications to 5,600 applications, so there are an extra 5,900 patents. Columns three and four show that OLS estimated effects of changing responses are qualitatively similar to negative binomial estimated effects.

Our counterfactuals find that US university responses diminish patenting for US companies, while US company responses increase patenting for US universities. Company responses ensure greater innovation given the portfolio characteristics of companies and universities. Their advantage occurs both in relation to the financial external dependence of innovation projects, and other factors including market demand.

8. Conclusion

In this paper we have looked at how the innovator type affected innovation during the 2007-8 financial crisis. Our theoretical and empirical results indicate that, at the start of the crisis, the effect of external financial dependence on the change in patent counts was insignificant for projects undertaken by companies but significantly positive for projects undertaken by universities. Higher proportions of intangible assets were associated with increased university patenting. The effects were similar over the 2008-9 period, although external financial dependence gained a significant positive association with company patenting. Similar effects are shown for innovative projects in technology classes introduced before 1991; the results for newer classes are not as strong but may be influenced by a relatively small sample size.

Counterfactuals indicate that if US company patenting responded in the same way as university patenting its decline would have been greater. Conversely, US universities would have had smaller declines if they had the same patenting response as US companies. We have not considered the possibility of innovation portfolio characteristics being selected in response to the funding used, which would alter counterfactual patent count changes. An analysis of endogenous selection could start from the theoretical basis described in the managerial literature on multiple interactions and influences between enterprise capabilities, competitive environment, and strategy (Henderson and Mitchell, 1997).

Our results echo those of Paunov (2012), who found that use of public funds by Latin American companies was associated with less discontinuation of their innovative projects during the crisis, whereas use of private funds was not significantly associated with it. Our data inspection and theoretical model suggest that the results can be explained by the increase of aggregate public R&D funding and moderate persistence of aggregate private R&D funding, at least in the US. The question then arises, why did private innovation funding not collapse during the crisis? Campello et al (2010) present a possible explanation, by finding that while total international company investment did fall sharply during the crisis, capital investments were relatively robust. Future work could establish whether innovation projects are accorded a protected status during crises, and whether particular types of projects are given more protection than others.

Although we did not dwell on the matter in the main text, it is interesting to note that persistence of innovation in each patent class was much higher for companies than for universities. One possible explanation is that universities are more willing to break radically with their past innovation during crises, perhaps acting as agents of creative destruction to a greater extent than companies (see Archibugi et al (2013a) and Archibugi et al (2013b)). Universities may have fewer institutional constraints stopping them from becoming radical innovators. However, groundbreaking innovations may be put by the USPTO into the same patent class as less significant innovations in the short term, because of delays in introduction of new classes. So short term patent classification is an imperfect way of recognising technological shifts. Moreover, an alternative institutional explanation for the persistence gap is possible, in that universities are able to retreat from the market in a way that is not possible for companies. Further study could clarify the reasons for the gap.

Our theoretical and empirical results suggest policy applications relating to the selection of solutions to informational and control problems in the principal-agent relations that arise in innovation. Solutions using financial markets may be susceptible to collapse during financial crises, and when they occur or are threatened it may be preferable to adopt elements of the non-market solutions used in university funding by industry or government, including direct or peer monitoring rather than commercially intermediated monitoring, and sharing technologies and profits between the funding and funded parties. However, the value of these relations during a crisis is dependent on the political commitment to fund innovation. If this commitment is lacking – which it generally was in crises prior to 2007-8 – then university relations may perform worse than company relations as funding conduits. Moreover, even during the crisis of 2007-8, company commercial innovative outputs were maintained at a higher level than university outputs. If maintenance of such outputs is sought by policymakers, universities could learn from the productive process of companies during crises. We leave it to future work to determine the exact nature of the lessons.

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