THE DIFFUSION OF COMPLEMENTARY TECHNOLOGIES: AN EMPIRICAL TEST

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Abstract

We analyze the simultaneous diffusion of multiple process technologies that are related. A new econometric model is used to investigate the presence of complementarities, testing for strong one-step-ahead non-causality and strong simultaneous independence. Results indicate significant complementarities between CAD and CNC technologies. Prior adoption of either of the two technologies has a large effect on the posterior adoption of the other one; in addition, simultaneous adoption is found to be more likely than adoption of the two technologies in isolation. Consistent with the presence of complementarities, we also find evidence of substantial price cross-effects: a decrease in the price of CAD (or CNC) increases the adoption probability of CNC (or CAD). Lastly, the increase in the likelihood of adopting the complementary technology turns out to depend on several plant-specific moderating factors.

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1. Introduction

The aim of this paper is to study the diffusion of bundles of allegedly complementary technological innovations using a new and powerful empirical model. We explore empirically whether two process technologies, Computer Aided Design (CAD) and Computer Numerically Controlled Machine Tools (CNC), that have been argued to be complementary (Jaikumar, 1986; Milgrom and Roberts, 1990; Colombo and Mosconi, 1995) do indeed exhibit complementarities in their adoptions. We further explore the determinants of those complementarities. We adopt the general economic framework of Stoneman and Kwon (1994) for analyzing the determinants of the return to the adoption of multiple technologies that may exhibit complementarities. In this framework, the complementarities are expressed as an increase in the per annum gross profit from adopting both technologies over and beyond the per annum gross profit from adopting the two technologies in isolation from each other.

In this paper, a new econometric model developed by Mosconi and Seri (forthcoming) is used to investigate the adoption of CAD and CNC by US manufacturing plants. The decisions to adopt the two technologies under consideration are modeled as a bivariate discrete-time binary process. There are some appreciable advantages of using this model over previous attempts at estimating complementarities (e.g., Stoneman and Kwon, 1994; Colombo and Mosconi, 1995; Stoneman and Toivanen, 1996). In particular, we are able to control more effectively for unobserved heterogeneity across plants and for the associated endogeneity bias, which may have led to inconsistent estimates in previous studies (see Athey and Stern, 1998). In addition, testing for the presence of complementarities between two technologies is quite direct using this model. It allows for testing strong simultaneous independence and strong one-step-ahead (Granger) non-causality; if the tests are rejected, adoption of both technologies (simultaneously or one after the other) is more likely than adoption of either technology in isolation. In addition, if technologies are complementary, the variables that directly affect the adoption probability of a given technology (e.g., the price of the technology) should have indirect cross-effects on the complementary technology. The model also allows us to explore whether the extent of complementarities depends on moderating factors.

We find significant complementarities between CAD and CNC technologies. Prior adoption of either of the two technologies results in an increase in the likelihood of adopting the other. In addition, simultaneous adoption of the two technologies is found to be more likely than adoption of either individual technology in isolation. We also find evidence of substantial cross-effects relating to the price of the complementary technology. Lastly, we highlight that the increase in the likelihood of adopting either CNC or CAD once the other technology is in place depends on various plant-specific factors.

The next section develops an empirical model summarizing the impact of a set of variables on a firm's decision to adopt two complementary technologies. Section 3 describes the data, section 4 explains the estimation methods and the variables, section 5 presents results and discusses interpretation concerns, and section 6 concludes.

2. An empirical model of the adoption of complementary technologies

The aim of this Section is to illustrate an empirical model predicting the effects of a set of variables on a firm's decision to adopt two complementary technologies (A and B). We follow previous literature (e.g., Karshenas and Stoneman, 1993) in distinguishing between rank, stock, order, and epidemic effects. Rank effects describe differences across firms. Stock effects relate to the expected decrease in the profits for an adopter generated by an increase over time in the number of competitors using the technology. Order effects relate to differences in profit gains from adoption derived from the firm’s position in the order of adopters at adoption time, with the assumption that first-mover advantages make early order more attractive. Epidemic effects capture the increases in the profit gains from adoption that arise from greater available information on the new technology, the latter being positively related to the number of adopters.

Let $g^j(\tau,t)$, j=A,B be the yearly operating profit gain at time τ from adoption of technology j alone at time t. Define $g^{AB}(\tau,t^A,t^B)$ as the yearly operating profit gain at time τ from adoption of technology A at time t^A and technology B at time t^B, with $\tau \geq t^A$ and $\tau \geq t^B$, relative to no use of the two new technologies. We then specify g^{AB} as:

$$g^{AB}(\tau,t^A,t^B) = g^A(\tau,t^A) + g^B(\tau,t^B) + v \quad . \qquad (1)$$

We define the two technologies as complementary if $v>0$ (Stoneman and Kwon, 1994). It also may be useful to differentiate between gains from simultaneous adoption and gains from sequential adoption. Let v^S and v^{jh} indicate the synergistic gains from simultaneous adoption and from adoption of technology j for a firm that has already installed technology h, respectively. For the sake of simplicity, let us assume v^S, v^{AB} and v^{BA} to be constant over time.

Let $N^j(\tau)$ represent the number of adopters of technology j, j=A,B at time τ. In accordance with previous studies, we assume the g^js to depend on variables that reflect rank ($X(\tau)$), stock ($N^A(\tau)$, $N^B(\tau)$), order ($N^A(t)$, $N^B(t)$), and epidemic effects ($N^A(\tau)$, $N^B(\tau)$). Therefore, we obtain:

$$g^j(\tau,t) = g^j[X(\tau), N^A(\tau), N^B(\tau), N^A(t), N^B(t)] \qquad j=\text{A,B} \qquad (2)$$

We indicate with $\partial g^j/\partial k$ the derivatives of the g^j functions with respect to term k. If stock and order effects are present, we expect:

$$\partial g^j/\partial N^h(\tau)<0;\ \partial g^j/\partial N^h(t)<0 \qquad j,h=\text{A,B}. \qquad (3)$$

Epidemic effects imply:

$$\partial g^j/\partial N^j(\tau)>0 \qquad j=\text{A,B}\ . \qquad (4)$$

Note that stock and epidemic effects are captured by the same variables but suggest opposite predictions as to their effects on the g^js. On the contrary, there are no specific predictions as to the signs of $\partial g^j/\partial x^k(\tau)$, *j*=A,B, which depend on the specific variable x^k included in the vector X. Following previous literature, we assume that the derivatives of the g^j functions are time invariant.

Let us indicate with $p^j(t)$ the price at time t of the capital good that embodies technology *j*, *j*=A,B. Both $p^A(t)$ and $p^B(t)$ are assumed to fall over time. As is usual in the inter-firm diffusion literature, we assume that a firm can adopt a new technology by purchasing a single unit of the capital good that is infinitely long lived, and that adoption decisions are irreversible.

Firms are assumed to have perfect foresight. Hence, a firm will adopt a new technology at time t if the benefit of waiting for a period dt is lower than the associated cost. Let us first consider a firm *i* that has not adopted either of the two new technologies under consideration. Following Stoneman and Kwon (1994), we indicate with $y_i^{A/O}(t)$, $y_i^{B/O}(t)$, and $y_i^{AB/O}(t)$ the difference between the benefits and the costs for the firm of waiting until (t+dt) before adopting technology A alone, technology B alone, or jointly adopting both

$$y_i^{A/O}(t) = rp^A(t) - \frac{dp^A(t)}{dt} - g_i^A[\mathrm{X(t), N^A(t), N^B(t)}]$$
$$+\frac{1}{r}\left[\frac{\partial g_i^A}{\partial N^A(t)}\frac{\partial N^A(t)}{\partial t} + \frac{\partial g_i^A}{\partial N^B(t)}\frac{\partial N^B(t)}{\partial t}\right]$$

technologies. Denoting with r the interest (discount) rate at time t, this results in:

$$y_i^{B/O}(t) = rp^B(t) - \frac{dp^B(t)}{dt} - g_i^B[\mathrm{X(t), N^A(t), N^B(t)}]$$
$$+\frac{1}{r}\left[\frac{\partial g_i^B}{\partial N^A(t)}\frac{\partial N^A(t)}{\partial t} + \frac{\partial g_i^B}{\partial N^B(t)}\frac{\partial N^B(t)}{\partial t}\right] \qquad (5)$$

$$y_i^{AB/O}(t) = rp^A(t) - \frac{dp^A(t)}{dt} + rp^B(t) - \frac{dp^B(t)}{dt} - g_i^A[\mathrm{X(t), N^A(t), N^B(t)}]$$
$$-g_i^B[\mathrm{X(t), N^A(t), N^B(t)}] - v^S + \frac{1}{r}\left[\frac{\partial g_i^A}{\partial N^A(t)}\frac{\partial N^A(t)}{\partial t} + \frac{\partial g_i^A}{\partial N^B(t)}\frac{\partial N^B(t)}{\partial t}\right]$$
$$+\frac{1}{r}\left[\frac{\partial g_i^B}{\partial N^A(t)}\frac{\partial N^A(t)}{\partial t} + \frac{\partial g_i^B}{\partial N^B(t)}\frac{\partial N^B(t)}{\partial t}\right].$$

Note that:

$$y_i^{AB/0} = y_i^{A/0} + y_i^{B/0} - v^S. \qquad (6a)$$

Let us now indicate with $y_i^{j/h}(t)$ the difference between the benefits and the costs of waiting until (t+dt) before adopting technology *j* for a firm that has previously adopted technology *h*, *j,h*=A,B, *j*≠*h*. We then obtain:

$$y_i^{A/B}(t) = y_i^{A/0}(t) - v^{AB}$$
$$y_i^{B/A}(t) = y_i^{B/0}(t) - v^{BA}. \qquad (6b)$$

According to expression (6a) and (6b), if the synergistic gains *v* are positive, there is an additional net profit gain from the adoption of technology *j*, *j*=A,B when the other technology is in place.

Following previous literature, we assume that unobserved factors may randomly influence the net profit gains from adoption of the two technologies under consideration. If we incorporate these factors into the model through a series of independent stochastic error terms, then from expressions (5) and (6) we can derive predictions as to the determinants of the adoption probabilities of the two technologies.

In particular, we are interested in sufficient conditions for the two technologies to be complementary. First, suppose that with all else equal, adoption of technology *j*, *j*=A,B becomes more likely after adoption of the other technology. Then, we derive $y_i^{j/h}(t) < y_i^{j/0}(t), (j, h = A, B, j \neq h)$ and, from expression (6b), $v^{jh}>0$. There is a synergistic gain from joint use of the two technologies; that is, the two technologies are complementary.

Let us now consider a firm that is using old vintage technologies (i.e., it has not adopted either of the two technologies under consideration). If simultaneous adoption of the two technologies turns out to be more likely than adoption of either individual technology in isolation, then $y_i^{AB/O}(t) > y_i^{A/0}(t) + y_i^{B/0}(t)$. From (6b), we then obtain $v^S>0$.[1]

Lastly, with two complementary technologies, the likelihood of adopting either of them will increase with an increase of the value of variables that positively affect the adoption probability of the other. For example, consider the effect of a decrease over time in the price p^B of technology B, with the price p^A of technology A held constant. Suppose initially that the values of p^A and p^B are such that $y_i^{A/0}>0$, $y_i^{B/0}>0$, and $y_i^{AB/0}>0$. So, it is unprofitable for a firm to install the two technologies both jointly and in isolation. If $v^S > y^{A/0}$, as the value of p^B declines over time the firm will move to a state where $y_i^{AB/0}<0$ and $y_i^{B/0}>0$. Then it will become profitable for the firm to install both technologies. Hence, due to complementarity, the likelihood of adopting technology A increases as p^B decreases. It follows that cross-effects can be interpreted as indirect evidence of complementarities.

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[1] The above arguments crucially rely on the assumption that the error terms in equation (6) are independent. This implies that unobserved factors do not affect the pattern of adoption of the two technologies. We will re-examine this issue in greater detail in Section 5.2.

It is important to emphasize that even if two technologies are complementary, they need not be adopted simultaneously. Suppose that ν^S, ν^{AB} and ν^{BA} are positive and the initial values of p^A and p^B make adoption of the two technologies unprofitable, both jointly and in isolation. Suppose further that the price of technology B declines more rapidly over time than that of technology A. Then a firm may move to a state where $y_i^{B/0}<0$. If $y_i^{A/0}$ and ν^S are such that $y_i^{AB/0}>0$ (i.e. $y_i^{A/0}>>\nu^S$), the firm will adopt technology B alone, in spite of the existence of complementarities between the two technologies. Subsequently, if the price of technology A further declines, the firm may find it profitable to adopt also technology A. As $\nu^{AB}>0$, this event is likely to occur earlier than in the absence of complementarities between the two technologies.[2]

What remains is to introduce reasonable instruments for the terms in equations (5), collect data, and specify the econometric model that will test the existence of complementarities.

3. Data and sources

To test the predictions illust*f*rated in the previous Section, a national mail survey was administered to plant managers using an address register from Dun and Bradstreet, followed up with a telephone survey. Following previous research results (Karshenas and Stoneman, 1993; Åstebro, 2002), we focus on plant-level characteristics as firm-level characteristics have been found generally not to be predictive of technology adoption. The telephone survey targeted plant technology specialists (one for each technology) with detailed technology-use questions.[3] The survey was conducted in 1993 and requested information about conditions at the plant and firm in 1992, in 1987, and, if applicable, at the time of adoption of CAD and/or

[2] Thus, even relatively long adoption lags between two technologies may be due to complementarities.

[3] For details on the survey's design, see Åstebro (2002).

CNC. The adjusted sample population consisted of 1,569 manufacturing plants representing 26 randomly selected metalworking industries. While 349 questionnaires were returned, 330 had usable data on outcome variables, representing an adjusted overall response rate of 21%.

CAD and CNC are of general interest as examples of technologies that have wide application in the manufacturing sector. They have been reported to have independent positive effects on productivity (e.g., Ewers, Becker, and Fritsch, 1990; King and Ramamurthy, 1992; Stoneman and Kwoon, 1996). It also has been reported that even greater productivity increases are possible if the two technologies are used in combination (Milgrom and Roberts, 1990; Colombo and Mosconi, 1995). The purported advantages relate to computerized integration between the design and manufacturing functions such that prototypes can be developed more rapidly, production can be set up more quickly, and customers' changing demand requirements can be fulfilled more effectively. Other complementary benefits include reduced or eliminated labour for transferring information between the design and manufacturing functions.

CNC and CAD initially spread slowly. The first adoption of CNC in the sample was in 1971, while it was in 1974 for CAD. In 1983, CAD's penetration was only 4% while CNC's penetration was 16%. The technologies exhibited rapid diffusion in the late 1980s. By 1993, CAD had been adopted by 54% of the plants as a result of rapidly declining computer prices, while 44% had adopted CNC. 34.6% of all adopters adopted CAD between 1989 and 1991. 29.8% of all CNC users adopted it first between 1987 and 1989. In 1993, 57% of CAD and 50% of CNC adopters had at least partial computer integration between CAD and CNC.

For the analysis of complementarities, the sample can be divided into four main groups: (i) those that by survey time had adopted neither technology: 110 plants (33.3%); (ii) those that only adopted CNC: 31 plants (9.4%); (iii) those that only adopted CAD: 69 plants

(20.9%); and (iv) those that adopted both CNC and CAD: 120 plants (36.4%). These data suggest that there might be complementarities since joint adoption is more prevalent than single technology adoption. For group (iv), we have data on the time of adoption for 95 plants. These 95 plants can be subdivided into: (iv *a*) those that adopted the two technologies simultaneously: 15 plants (15.8%); (iv *b*) those that adopted CNC before CAD: 60 plants (63.2%); and (iv *c*) those that adopted CAD before CNC: 20 plants (21.0%). The adoption lags between the two technologies, when both are adopted, are relatively short but not immediate. The average adoption lag when CNC is adopted before CAD is 5.85 years, (st. dev.= 3.83) and the average adoption lag when CAD is adopted before CNC is 2.30 years, (st. dev.= 1.63).

A list of variables and definitions is provided in Table 1. Price data on CAD were not directly available. We know however that significant drops in quality-adjusted price occurred following the introduction of the minicomputer and personal computer in 1977 and 1981, respectively (Åstebro, 1992). Therefore, it seems reasonable to use as a proxy the price of computers and peripherals, obtained from BEA (NIPA, Table 7.8, row 37). The price of CNC was obtained from Paul Stoneman and Giuliana Battisti, who have used this index in several publications. CNC prices were transformed from pounds sterling to U.S. dollars using Federal Reserve Board (FRB) publications. For interest rates, we used the FRB-published three-month T-bill rate. All prices and costs were adjusted with the producer price index published by BEA (NIPA, Table 7.1). Estimates of size-of-industry demand and growth of demand were derived from yearly data on industry sales provided by the NBER (www.nber.org/nberces/nbprod96.htm). This source also provided data on by-year, by-industry production and non-production wage rates. We obtained information on industry concentration (CR4) from the Census of Manufacturing Bulletin, Concentration Ratios in

Manufacturing, 1974-1992. In between census years, we assigned values using linear interpolation. When data were missing prior to 1987 (SIC 3492, 3591, 3593, 2594, 3599), we assigned CR4s as given by 1987 values. Various plant-level data were obtained from the survey.

4. Specification of the econometric model

4.1. The econometric model

The specification of the econometric model is based on Mosconi and Seri (forthcoming). We model the decisions to adopt the two technologies under consideration as a bivariate discrete-time binary process $Y_t=\{Y^A_t, Y^B_t\}$. In particular:

$y^A_{i,t}=1$ if plant *i* is an adopter of CNC at time t

$y^B_{i,t}=1$ if plant *i* is an adopter of CAD at time t

with $t=[t^E_i \ldots.. T]$.

t^E_i is plant's *i* year of entry, while T is the last year of the observation period (i.e., 1993). At any time t, the state space of Y_t includes four states: 0={0,0}, A={1,0}, B={0,1}, and AB={1,1}. Plants in state 0 adopted neither of the new technologies. Plants in state A and B adopted either CNC or CAD, respectively. Joint adopters are in state AB. The model is represented by the diagram in Figure 1: each block corresponds to one of the four possible states, while arrows indicate transitions between states. Y_t is assumed to be a first-order Markov process.

In accordance with the latent regression approach, we assume that plant *i* adopts technology *j*, *j*=A,B if a latent continuous random variable $y^{*j}_{i,t}$ crosses a threshold level, which with no loss of generality is set equal to 0. Furthermore, $y^{*j}_{i,t}$ is assumed to depend on the state in which plant *i* is in time t-1 and a set of covariates $x_{i,t}$. We also consider the interaction between the covariates and the states of the process in t-1; in other words, the effects on $y^{*j}_{i,t}$ of the covariates may be state-contingent. Hence, for a plant that has adopted neither CNC nor CAD (that is, it is starting from state 0), the latent regression system is:

$$\begin{cases} y_{i,t}^{*A} = \beta_{A1}^T x_{i,t} + \varepsilon_{i,t}^A \\ y_{i,t}^{*B} = \beta_{B1}^T x_{i,t} + \varepsilon_{i,t}^B \end{cases}$$

As is usual in this setting, we assume a standardized bivariate normal distribution for $(\varepsilon^A_{i,t}, \varepsilon^B_{i,t})$:

$$\begin{pmatrix} \varepsilon_{i,t}^A \\ \varepsilon_{i,t}^B \end{pmatrix} \sim iidN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{i,t} \\ \rho_{i,t} & 1 \end{bmatrix} \right)$$

with

$$\rho_{i,t} = \frac{2e^{\gamma^T x_{i,t}}}{1 + e^{\gamma^T x_{i,t}}} - 1.$$

It follows that the transition probabilities $h_i^{j/0}(t)$ of moving to state *j*, j=A,B,AB at time t, provided that plant *i* is in state *0* in time t-1, can be modeled through a bivariate probit model. This results in:

$$P\{y_{i,t} | Y_{i,t-1} = \{0\}, x_{i,t}\} = \Phi_2 \left(\begin{bmatrix} \beta_{A1}^T x_{i,t} \\ \\ \beta_{B1}^T x_{i,t} \end{bmatrix}; 0, \begin{bmatrix} 1 & \rho_{i,t} \\ \\ \rho_{i,t} & 1 \end{bmatrix} \right) \tag{7}$$

With respect to transitions from state A to state AB, the only latent regression concerns adoption of technology B and can be written as:

$$y_{i,t}^{*B} = \beta_{B1}^T x_{i,t} + \beta_{B2}^T x_{i,t} + \varepsilon_{i,t}^B$$

giving rise to the univariate probit model

$$P\{y_{i,t}^B | Y_{i,t-1} = \{A\}, z_{i,t}\} = \Phi_1 \left(\beta_{B1}^T x_{i,t} + \beta_{B2}^T x_{i,t}; 0, 1 \right) \tag{8a}$$

The same holds for the passage from B to AB, as defined by the latent regression model

$$y_{i,t}^{*A} = \beta_{A1}^{T} x_{i,t} + \beta_{A2}^{T} x_{i,t} + \varepsilon_{i,t}^{A}$$

Hence:

$$P\left\{y_{i,t}^{A} \middle| Y_{i,t-1} = \{B\}, z_{i,t}\right\} = \Phi_{1}\left(\beta_{A1}^{T} x_{i,t} + \beta_{A2}^{T} x_{i,t}; 0, 1\right) \tag{8b}$$

In this framework, we are interested in testing for the presence of complementarity effects between the two technologies under consideration. For this purpose, we have to test for strong simultaneous independence and strong one-step-ahead non-causality. In particular, if the null hypothesis that Y^{A}_{t} and Y^{B}_{t} are strongly and simultaneously independent is rejected, simultaneous adoption of both technologies is more or less likely than adoption of either individual technology, according to the positive or negative sign of ρ. This hypothesis can be tested through a Wald test for the parameters included in the vector γ, which drives the correlation coefficient ρ. If the null hypothesis that Y^{A}_{t-1} (Y^{B}_{t-1}) does not strongly cause Y^{B}_{t} (Y^{A}_{t}) one-step-ahead is rejected, then the likelihood of adopting technology B (A) increases after adoption of the other technology. This hypothesis can again be tested through a Wald test for the parameters included in the vector β_{B2} (β_{A2}). Furthermore, if the two technologies are complementary, we expect variables included in the vector X that directly influence the adoption probability of one technology to have effects on the adoption probability of the other technology.

4.2. Econometric adjustments

We expected fewer responses from smaller plants. Survey responses were regressed on various predictors. There were significant variations in response rates. Responses were therefore weighted with the inverse of the predicted response frequency for each response. Use of this method is supported, for example, by Holt et al. (1980).

The model illustrated in the previous section is estimated on data organized into time-series cross-sectional panels. In the empirical analysis, we initially estimate by maximum likelihood the bivariate probit model described by equations (7) and (8) while replacing the vectors γ, β_{A2}, and β_{B2} with intercept parameters γ_0, $\beta_{A2,0}$, and $\beta_{B2,0}$. In other words, we assume synergistic gains not to depend on any of the covariates included in the vector X. Hence, the null hypotheses of strong simultaneous independence and strong one-step-ahead non-causality, indicating that there is no complementarity between CNC and CAD, are as follows:

i) Y^A_t and Y^B_t are strongly simultaneously independent given Y_{t-1} iff $\gamma_0=0$

ii) Y^B_{t-1} does not strongly cause Y^A_t one-step-ahead iff $\beta_{A2,0} = 0$

iii) Y^A_{t-1} does not strongly cause Y^B_t one-step-ahead iff $\beta_{B2,0} = 0$

The reason for our conservative approach in specifying complementarity causes is that, based on previous theory and results, we can state with some degree of confidence the predictors of adopting CNC and CAD independently and jointly. However, much less is known about the predictors of the complementarities between these two technologies. It is also the case that there are fewer observations available to estimate the latter effects with precision.

In addition, we focus attention on cross-effects relating to price variables since we can state with confidence these expected cross-effects. Moreover, we extend the analysis to explore rank cross-effects. Finally, to avoid estimation problems, we delete from the analysis six industries that each had less than ten observations.[4]

4.3. The explanatory variables

Definitions of the explanatory variables are reported in Table 1. For a summary of predictions, see Table 2. The model outlined in section 2 predicts that the relative quality-adjusted real price of a technology and the expected decrease of this price decrease the probability of its adoption. If CNC and CAD are complementary, their prices and expected price changes also should decrease the probability of the other technology's adoption. Therefore, we predict negative and positive effects of rp^j and dp^j on the likelihood of adoption of both technologies.

Moving to rank effects as captured by vector X in equations (7) and (8), we distinguish between covariates that have a direct effect on the adoption probability of a given technology and those that have an indirect cross-effect, indicating that complementarity is at work. We further distinguish plant- and industry-specific effects. As to plant-specific direct effects, in accordance with previous studies (for a survey, see Stoneman, 2002) we predict that plant size (S) is a positive determinant of technology adoption. We also expect adoption of previous vintages of advanced manufacturing technology (i.e., numerically controlled machine tools, or NC) to provide learning opportunities that encourage the adoption of both CNC and CAD (Colombo and Mosconi, 1995; Åstebro 2002). Finally, we include two indicators of the benefits specific to CNC (B^{CNC}: machining tolerance of parts) and CAD adoption (B^{CAD}: number of design and/or engineering modifications); rationales for these can be found in Ewers, Becker and Fritsch (1990) and King and Ramamurthy (1992). If B^j (j=CNC, CAD) also influence adoption of the other technology (that is, they exhibit negative and positive cross-effects, respectively), this fact is interpreted as evidence of complementarities between the two technologies.

Following standard industrial economics literature (Stoneman, 2002), we include industry-specific rank effects as follows: a measure of market size (M), growth in demand (G), and the four-firm concentration ratio (CR4). Technology adoption is expected to be

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[4] Missing data for predictors were imputed using regression. For further information, see Åstebro (2004). We constructed a dummy variable whenever an observation was imputed and included that in regressions. None of these dummy variables were important or significant.

positively related to M and G, while there is no strong expectation on the sign for CR4. We also consider the ratio of the wage rate of non-production workers to that of production workers (WR). Computer-based technologies reportedly replace workers involved in standardized, procedural tasks, while they allegedly complement tasks that require greater cognitive skills (Bresnahan et al., 2002). To the extent that tasks performed by production (blue-collar) workers more frequently belong to the former category relative to those of non-production (white-collar) workers, the demand for the two technologies under consideration should increase when the salaries of non-production workers are low relative to those of production workers (for a similar argument in a different context, see Caroli and Van Reenen, 2001). Hence, we predict that WR will negatively affect the likelihood of adoption of CNC and CAD. Following Åstebro (2002), we suggest that the expected non-capital sunk costs of adoption (SC^j) discourage technology adoption. This measure is implemented as a cross-industry effect in this study.

To capture stock and order effects, we use the number of adopters of CNC and CAD (N^j) measured at time t-1 so as to alleviate endogeneity problems and the expectation of the change in the number of users of the technology between t+1 and t (dN^j) in the industry in which a plant operates. Following the game-theoretic literature, we would expect these variables to relate negatively and positively to technology adoption, respectively. However, it is possible that N^j also captures epidemic effects associated with information diffusion. If these latter effects dominate, the sign of this variable may be reversed.[5] Nevertheless, when more than one technology is being diffused, there are additional (direct and indirect)

[5] This indeterminacy (due to use of the specific proxy measures) has plagued past attempts at estimating stock/order effects. At best, only weak stock/order effects have been found (for instance, see Karshenas and Stoneman, 1993).

stock/order cross-effects and (indirect) epidemic cross-effects that need to be taken into account.

Let us first consider direct cross-effects, neglecting indirect ones. If there are stock and order effects, lower expected profit gains from adoption of technology *j*, *j*=CNC, CAD leading to a decrease in the likelihood of adoption, are possibly determined by an increase over time in the number of users of the other technology (N^h, $h \neq j$). Conversely, direct effects arising from information diffusion are technology-specific. Furthermore, if CNC and CAD are complementary, there will be indirect cross-effects. Stock/order effects again suggest that the likelihood of adopting technology *j* declines with N^h and increases with dN^h, $h \neq j$. By contrast, indirect epidemic cross-effects predict a positive coefficient for N^h in the equation relating to the adoption probability of the other technology. In sum, if only epidemic effects are at work (i.e., there are no stock/order effects), both N^{CNC} and N^{CAD} should positively affect the adoption of the two technologies. Conversely, if there are stock/order effects but no epidemic effects, the sign of the coefficients of N^{CNC} and N^{CAD} should be reversed and dN^{CNC} and dN^{CAD} should exhibit positive coefficients. As there may be several effects at work simultaneously, it may turn out to be difficult to identify correctly the effects behind the estimates of the coefficients for N^j and dN^j, *j*=CNC, CAD.

5. Results

5.1. Estimations

Equations (7) and (8) have been jointly estimated by maximum likelihood estimation.[6] As was said earlier, we initially replaced vectors γ, β_{A2}, and β_{B2} with intercept parameters γ_0, $\beta_{A2,0}$, and $\beta_{B2,0}$, thus assuming that the extent of the complementarity effects does not vary across plants. Results are reported in Table 3. Results of tests for strong simultaneous independence

[6] Computations were performed using Ox 3.10 (Doornik, 2002).

and strong one-step-ahead non-causality (see Mosconi and Seri, forthcoming) are reported in the bottom part of Table 3.

Our primary results are as follows. The value of γ_0 is positive and statistically significant at 99%, rejecting the null hypothesis of strong simultaneous independence between y^{CNC} and y^{CAD}. The estimated value of the coefficient ρ representing the correlation between the error terms in the CNC and CAD equations is equal to 0.4539 and significant at 99%, indicating that simultaneous adoption of both technologies is more likely than adoption of either technology in isolation. In addition, the values of $\beta_{CNC,2}$ and $\beta_{CAD,2}$ are both positive and significant at 99%. We are therefore able to reject the null hypothesis that y^{CAD} (y^{CNC}) does not Granger cause y^{CNC} (y^{CAD}) one-step-ahead. In other words, the adoption of either of the two technologies under consideration positively influences the likelihood of subsequent adoption of the other. Altogether, these results suggest that there are sizable gains from joint use of the two technologies relative to the increase in profits that can be obtained through using either of them in isolation.

Further insights into the existence of complementarities can be provided by analyzing cross-effects. Here the evidence is mixed. As to cross-price effects, the null hypothesis that they are jointly null is rejected by a LR test at 99% ($\chi^2(4)=29.14$). In fact, both rp^{CAD} and rp^{CNC} have negative and statistically significant effects on the likelihood of adopting the other technology. Further, the coefficient for dp^{CAD} in the CNC equation, which captures the cross-price expectation effect, is significant and has the expected sign. But the coefficient for dp^{CNC} in the CAD adoption equation is not significant. Moreover, we do not find any evidence of rank cross-effects. The null hypothesis that the coefficients for B^{CAD} in the CNC equation and that for B^{CNC} in the CAD equation are jointly equal to 0 cannot be rejected by a LR test ($\chi^2(2)=0.63$).

Let us now turn our attention to the direct effects of the explanatory variables in the two equations. First, the results confirm the key role of the decline of prices for the diffusion of information technologies, as highlighted in previous studies (see Bresnahan et al., 2002 and references therein). As expected, the probabilities of adoption of CNC and CAD increase with a decrease in the own-price of the technology; both rp^{CNC} and rp^{CAD} have negative and significant coefficients in the CNC and CAD equations, respectively. Price expectations are also found to play a crucial role for the diffusion of CAD, with the coefficient of dp^{CAD} positive as predicted and significant at 99%. However, own-price expectations turn out to exert a negligible influence on the diffusion of CNC, possibly as a consequence of the less rapid decline in the price of CNC machine tools in comparison with that of computers.

Second, in line with the extant diffusion literature (reviewed in Stoneman, 2002), we find evidence of significant rank effects. Quite unsurprisingly, larger plants are more likely to adopt both CNC and CAD than smaller ones; the coefficients of S are positive and significant at conventional confidence levels in both equations. Previous adoption of NC equipment positively affects subsequent adoption probabilities of both CNC and CAD, as shown by the positive statistically significant coefficients of NC. This suggests that complementarities extend to previous vintages of both the same and related technologies. The result is also consistent with previous work (e.g., Colombo and Mosconi, 1995), which indicates that there are learning-by-using effects across different vintages of these technologies.[7] In the CNC equation, all remaining rank effects are insignificant with the exception of B^{CNC}, which has a positive coefficient as expected. In the CAD equation, in addition to B^{CAD}, the relative wage

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[7] In fact, the coefficient of NC is very large and highly significant in the CNC equation. We are aware that these results might suffer from an endogeneity bias. In principle, one could examine complementarities across M simultaneously diffusing technological innovations. Unfortunately, the estimate of a comprehensive multivariate discrete-time binary model is unfeasible due to the excessively large number of parameters. For instance, the case of three innovations would require us to compute 19 transition probabilities.

rate is close to significance. Its negative sign is consistent with the argument proposed by the skill-biased technical change literature (e.g., Bresnahan et al., 2002) that information technologies are a complement of highly skilled labor while they replace unskilled labor (see *infra*). Note however that the same argument seems not to apply to CNC. We regard the latter as a plausible result given that CNC machine tools primarily increase skills of blue-collar workers (see Åstebro, 2002).

With respect to stock, order, and epidemic effects, it is quite difficult to unambiguously interpret the results of the estimates as opposing forces may be at work.[8] N^{CAD} and N^{CNC} exhibit positive and highly significant coefficients affecting CAD and CNC adoption, respectively, providing evidence of the existence of direct epidemic effects. The same variables have negative coefficients in the equation relating to the other technology: the coefficient for N^{CAD} is significant at 99% in the CNC equation, while that for N^{CNC} is only close to significant in the CAD equation. This suggests that negative direct and indirect stock/order cross-effects prevail over indirect positive epidemic cross-effects. As to the dN^j (*j*=CNC, CAD) variables, their coefficients are insignificant; hence, there is no evidence of order effects (either direct or indirect).

Last, we explore whether the complementarities we detect are moderated by plant-specific rank effects. The results are quite interesting, even though they should be interpreted with care due to the limited number of observations. This caution applies especially to the simultaneous adoption of the two technologies where there are only 15 observations in that state. We therefore refrain from trying to interpret determinants of this state of adoption. Economic interpretation of coefficient estimates for the subsequent adoption of one

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[8] Some researchers have introduced lags since first industry adoption and/or first overall adoption to proxy for epidemic effects. We tried specifications with such proxies but were unable to obtain reasonable convergence properties and estimates due to strong multicollinearities with $N^j(t)$ and $(1/r)dN^j(t)$.

technology after the other is less tenuous since there are more observations for these states (60 and 20, respectively), although caution is still warranted.

Let us first consider the y^{CNC} equation. As reported at the bottom of Table 4, plant size has a positive statistically significant coefficient, indicating that the additional benefits from the integration of CNC for plants that have already adopted CAD over and above those arising from adoption of CNC alone are greater the greater the size of plants. The coefficient of NC, though positive, is insignificant. The same holds true for B^{CNC} and B^{CAD}. Let us now turn attention to the y^{CAD} equation. In Table 4, the coefficient for NC is negative and significant at 95%. Hence adoption of CNC leads to a smaller increase in the likelihood of subsequent adoption of CAD for plants that have previously adopted NC equipment. This suggests that NC and CNC equipments are substitutes as complements to CAD.[9] As opposed to the estimate reported directly above, plant size does not play any role for subsequent CAD adopion, possibly because, as opposed to CNC machine tools, CAD equipment is less expensive. The marginal cost-spreading effect of plant size on CAD-CNC integration when adding CAD equipment after CNC equipment then would be less pronounced than when adding CNC equipment after CAD. As to the remaining plant-specific rank effects, B^{CAD} has a positive coefficient and is significant at conventional confidence levels. This result suggests that the complementarity effects associated with the adoption of CAD once CNC is in place are positively influenced by the total amount of set-up costs; as these costs are likely to

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[9] The starting point is the positive and significant coefficient of NC driving the adoption of CAD alone (Table 3). This means that for plants that have not adopted CNC, adoption of NC equipment positively influences the likelihood of adoption of CAD due to complementarity effects. In addition, there are complementarities between CNC and CAD (positive β_0 coefficient): hence, the likelihood of adopting CAD increases after CNC adoption. The negative coefficient of NC in the beta vector then shows that the positive effect on CAD adoption engendered by the adoption of CNC is smaller if a plant had previously adopted NC equipment and so was already exploiting (to some extent) the complementarity effects between design and production equipment.

increase with the number of design and engineering modifications, we expect to see greater joint use of CAD and CNC to reduce these costs through computer integration.

5.2. Interpretation of tests

Unobserved heterogeneity may potentially affect our tests. There are two types of unobserved heterogeneity: cross-sectional and time varying. Cross-sectional unobserved heterogeneity arises because of unobserved time invariant factors that influence the likelihood of adoption of the two technologies under consideration. This type of unobserved heterogeneity may indeed affect the estimate of γ_0; conversely it may only affect the estimates of $\beta_{A2,0}$ and $\beta_{B2,0}$ in special cases, as these parameters capture the increase in the likelihood of adopting one technology when the other complementary technology is already in place. Cross-sectional unobserved heterogeneity may influence the estimates of $\beta_{A2,0}$ and $\beta_{B2,0}$ if a plant simultaneously decides to adopt both technologies but the introduction of one of them is postponed as capital budgeting constraints or convex adjustment costs prohibit simultaneous adoption. In this case we would expect sequential adoption of the two technologies with short adoption lags. While such concerns are valid, the adoption lags in our survey are typically longer than what would be expected if decision-makers planned the adoption sequence due to capital budgeting or convex adjustment costs. The time to reach 90% of efficient use is approximately six months after adoption for each of the two technologies (Astebro, 2002); so one would expect adoption lags to be one year if the adoption of one technology after the other was driven by cross-sectional unobserved heterogeneity combined with capital budgeting considerations or convex adjustment costs. However, most sequential adoptions are stretched out further in time with an average adoption lag of 5.0 years (see Section 3).[10]

[10] Another concern is that plants that adopt a technology grow due to the adoption. The increase in plant size may trigger the adoption of a second technology as the benefit of using the second technology has now

Time-varying unobserved heterogeneity may also affect the estimates of $\beta_{A2,0}$ and $\beta_{B2,0}$, in addition to that of γ_0. The two most plausible such factors are unobserved price or performance changes that are common to both technologies, for example a joint superprice of A and B that declines with time and is not completely measured by our price indexes. This should cause the probability of adopting both A and B to increase with time. Assume A but not B is adopted at time t due to a reduction in the superprice. The superprice continues to decline and later causes B to be adopted. There would thus be an increase in the probability of adopting B after A simply because of this unobserved price and not due to complementarities. There might exist such time-trend biases in the quality-adjusted price indexes we use.[11]

The econometric model was developed in order to test for Granger noncausality conditionally on a set of covariates. As was explained above, unobserved heterogeneity is driven by factors that are not captured by the explanatory variables of the model. So, as long as Granger non-causality (and not adoption complementarity) is being tested, unobserved heterogeneity is not relevant. Equating our tests of Granger noncausality with a test of adoption complementarities is justified most persuasively by the economic interpretations of the fact that the increase of the probability of adopting one technology when the other technology is in place, was found to depend on several covariates. Here is where our approach provides the largest improvement over previous attempts at estimating complementarities.

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increased. In this case the sequential adoption is due to endogeneity rather than unmeasured heterogeneity. There are two responses to this critique. The first is that the described endogeneity actually represents complementarities. A second response is that we examined this critique by instead measuring plant size at a fixed point in time, 1987. Plant size is thus pre-determined for all adoptions after 1987. We found that the coefficients for $\beta_{A2,0}$ $\beta_{B2,0}$ and γ_0 changed very litte, by 1.9%, -1.6% and -2.2%, respectively, indicating that the set of estimates reported in Tables are not affected by the potential endogeneity of plant size.

[11] A final concern may be unobserved common shocks (e.g. change in market conditions at time t) causing an instantaneous increase in the probability of adopting both technologies A and B. This case is similar to the cross-sectional unobserved heterogeneity case in that these shocks simply shift the intercepts of the unconditional probability of adopting both technologies but do not affect the difference between the conditional probability of adopting technology B (A) at time t given that technology A (B) was previously adopted and the conditional

We provide plausible economic rationales for how the covariates indicate complementarities. These tests are the strongest to date of large complementarities in adoption probabilities for these technologies.

6. Conclusions

The aim of this paper is to study the simultaneous diffusion of two allegedly complementary technological innovations. We have explored empirically whether CAD and CNC machine tools do indeed exhibit complementarities in their adoptions using a new and powerful empirical model and testing for strong one-step-ahead non-causality and strong simultaneous independence. The decisions to adopt the two technologies under consideration are modeled as a bivariate discrete-time binary process. There are some appreciable advantages of using this model over previous attempts at estimating complementarities. In particular, we are able to control more effectively for unobserved heterogeneity across plants and the associated endogeneity bias, which may have led to inconsistent estimates in previous studies.

Results indicate significant complementarities between CAD and CNC technologies. Prior adoption of either of the two technologies under scrutiny has a large positive effect on posterior adoption of the complementary technology, while simultaneous adoption is found to be more likely than adoption of either of the two technologies in isolation. Consistent with strong complementarities, we also find evidence of substantial price cross-effects: a decrease in the price of CAD (or CNC) increases the adoption probability of CNC (or CAD).

We also explore the sources of these complementarities. It has been suggested that joint use of CNC and CAD allows for more efficient data transfer between design and production. But theory is not very specific as to how these complementarities arise. For example, we do not have a clear idea whether these benefits are scale dependent or are

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probability of adopting B (A) given that A (B) was not. So we are quite confident that $\beta_{A2,0}$ and $\beta_{B2,0}$ are not influenced by other characteristics of plants. For this purpose, we investigate whether the extent of the detected complementarities is moderated by plant-specific rank effects. Results are encouraging, even though they should be interpreted with caution due to the limited number of available observations. In fact, we are able to highlight that the additional benefits from subsequent adoption of CNC or CAD, once the complementary technology is in place over and above those benefits that arise from adoption of CNC or CAD in isolation, do depend on plant-specific effects.

With respect to these plant-specific complementarities, we find that plant size has an interesting differential effect on the subsequent adoption of CNC and CAD. CNC adoption subsequent to CAD adoption is positively affected by plant size, while subsequent CAD adoption is not. We interpret this to mean that since CAD equipment is generally less expensive than CNC equipment, the cost-spreading benefit of size is more important for CNC than CAD posterior adoption. Supporting this interpretation is the fact that the coefficient for plant size is 50% larger for exclusive-use of CNC versus exclusive-use of CAD. Previous use of NC equipment also has an interesting differential effect on the adoption of CNC after CAD versus CAD after CNC. Previous use of NC equipment has a weak positive effect on adopting CNC after CAD, while it has a strong negative effect of adopting CAD after CNC. The former is interpreted as a learning effect – CNC adoption is made easier by the plant already knowing something about NC technology. The latter is interpreted as a substitution effect – plants having previously adopted NC equipment may already enjoy the advantages of joint use of complementary design and production technologies.

In our view, this work represents an important step forward in the empirical literature concerned with the diffusion of bundles of new technologies. It also opens the way to further

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overestimated for this reason, while the estimate of γ_0 is more exposed to this concern.

additions to this literature. Two avenues for future research seem especially promising. First, it has been convincingly argued (e.g., Milgrom and Roberts, 1990; Bresnahan et al., 2002) that the returns to the adoption of IT-based process innovations are contingent on the organization of plants (and firms). In fact, plants that exhibit a "lean" organization with a small number of managerial layers and highly decentralized decision-making and that use "high performance" human resource management practices allegedly are those that benefit the most from use of the above-mentioned technological innovations. In other words, technological and organizational innovations are complementary. The empirical model we have presented in this paper is suitable to rigorously test this proposition. For instance, Battisti et al. (2004) use a similar model to highlight the existence of complementarity effects between the adoption of CAD and an innovative management practice in design (i.e., the establishment of joint design teams with customers and/or suppliers). Second, our results regarding how the complementarities are moderated by plant-specific factors are only suggestive and much remains to be done in this area. Our estimates suffer from lack of a sufficient number of observations in our dataset, especially regarding the simultaneous adoption of the two complementary technologies. More importantly, our findings beg the question of a theory that explicates how the complementarities arise and that would guide an empirical formulation and estimation beyond that undertaken here.

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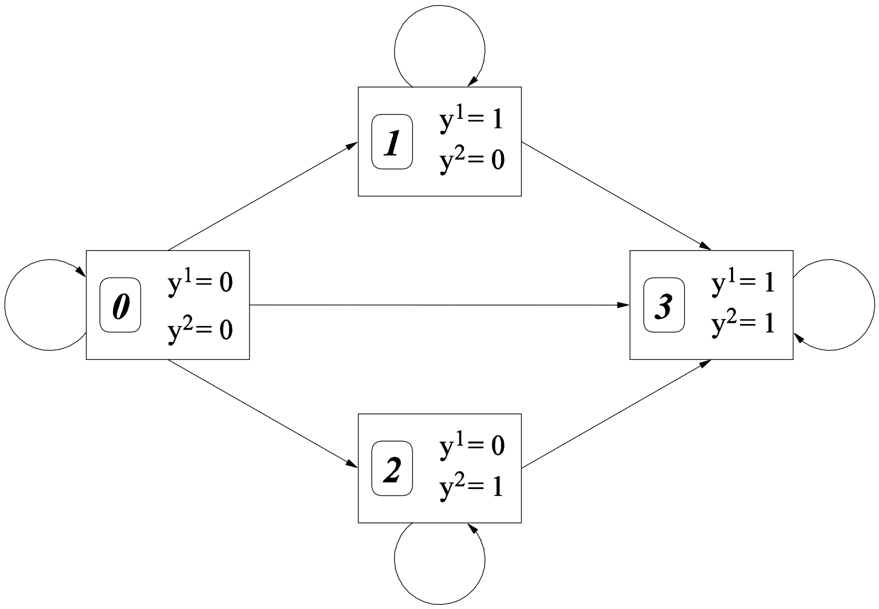

Figure 1 - The state space of the Markov process for Y_t

Table 1: Notation and definition of covariates

Variable	Definition
$rp^j(t)$	Price index of technology j in U.S. $, at time t multiplied by the discount rate (measured by yield on 90-day Treasury Bills) and divided by Producer Price Index (PPI)
$dp^j(t)$	Expected percentage change in the price index of technology *j* at time t (price is divided by PPI)
M(t)	Market demand for the industry to which plant i belongs, measured by Q(t), divided by industry-specific PPI
G(t)	Change in demand for the industry to which plant i belongs, measured by Q(t+1)-Q(t), where Q(t) is total sales of the industry at time t, divided by industry-specific PPI
CR4(t)	Concentration ratio in the industry to which plant i belongs, measured by the percentage share of gross output of the four largest firms in the industry at time t
WR(t)	Ratio of the wage level of non-production workers to the wage level of production workers in the industry to which plant *i* belongs at time t
S(t)	Size of the plant i, measured as log(q+1) where q is plant output in 1992, or plant output in 1987 if t<= 1987, or q is a linear interpolated value of output between 1987 and 1992 if 1987<t<1992.
NC(t)	Previous adoption of NC equipment, = 1 at time of NC adoption and onwards, 0 otherwise for plant i
SC^j	Sunk costs of adoption of technology j, measured as industry average time spent on investment decision and industry average time spent learning to operate the technology before reaching 90% of its technical capability, both divided by extent of in-plant use of technology. Principal components analysis was used on the standardized values and a score was computed using the loadings on the first eigenvector.
B^{CAD}	Benefit to CAD use, measured as number of design and/or engineering modifications made by plant i of its major product line in 1992
B^{CNC}	Benefit to CNC use, measured as closest machining tolerance of parts for major product line of plant i in 1992
$N^j(t)$	Number of plants in the industry owing technology j at time t
$(1/r)dN^j(t)$	Expected change in the cumulative number of adopters of technology j in the interval (t+1,t), measured as $[N^A(t+1)- N^A(t)]$, divided by the discount rate

Notes: For more details on SC^{CAD} and SC^{CNC}, see Åstebro (2004).

Table 2: Expected effects of covariates on the likelihood of adoption of CNC and CAD

Variable	CNC		CAD	
	Direct effect	**Indirect effect**	**Direct effect**	**Indirect effect**
rp^{CNC}	-		/	-
dp^{CNC}	+		/	+
rp^{CAD}	/	-	-	
dp^{CAD}	/	+	+	
G	+		+	
M	+		+	
CR4	?		?	
WR	-		-	
NC	+		+	
S	+		+	
SC^{CNC}	-		/	-
SC^{CAD}	/	-	-	
B^{CNC}	+		/	+
B^{CAD}	/	+	+	
N^{CNC}	-/+[a]		-[a]	-/+[a]
$(1/r)dN^{CNC}$	+		/	+
N^{CAD}	-[a]	-/+[a]	-/+[a]	
$(1/r)dN^{CAD}$	/	+	+	

Notes: a) -: stock/order effect; +: epidemic effect

Table 3: Estimates of the CNC and CAD adoption model

	CNC				CAD			
	β_{CNC}	σ_{CNC}	*t test*	*p*	β_{CAD}	σ_{CAD}	*t test*	*p*
Const	-2.1443	0.4459	-4.8086	0.0000	-1.5528	0.3857	-4.0260	0.0001
rp^{CNC}	-0.0358	0.0192	-1.8586	0.0631	-0.0514	0.0240	-2.1387	0.0325
dp^{CNC}	-0.3613	0.2973	-1.2154	0.2242	-0.1760	0.3419	-0.5149	0.6066
rp^{CAD}	-0.0024	0.0006	-3.9586	0.0001	-0.0043	0.0011	-3.9735	0.0001
dp^{CAD}	1.0008	0.4737	2.1129	0.0346	1.8282	0.5818	3.1423	0.0017
M	0.0045	0.0063	0.7058	0.4803	-0.0063	0.0056	-1.1142	0.2652
G	-0.0210	0.0358	-0.5880	0.5565	0.0307	0.0579	0.5297	0.5963
CR4	-0.0023	0.0018	-1.2900	0.1971	-0.0020	0.0018	-1.1389	0.2547
WR	-0.1689	0.2118	-0.7976	0.4251	-0.2592	0.1702	-1.5232	0.1277
S	0.0288	0.0097	2.9682	0.0030	0.0241	0.0122	1.9835	0.0473
NC	0.8278	0.0848	9.7667	0.0000	0.1743	0.0902	1.9319	0.0534
SC^{CNC}	-0.0241	0.0585	-0.4122	0.6802	-0.0673	0.0468	-1.4376	0.1506
SC^{CAD}	-0.0324	0.0471	-0.6865	0.4924	-0.0016	0.0422	-0.0378	0.9699
B^{CAD}	-0.0060	0.0151	-0.3965	0.6917	0.0645	0.0145	4.4419	0.0000
B^{CNC}	0.0999	0.0260	3.8463	0.0001	-0.0182	0.0266	-0.6855	0.4931
N^{CNC}	0.1493	0.0176	8.4614	0.0000	-0.0649	0.0172	-3.7802	0.0002
N^{CAD}	-0.1400	0.0209	-6.6958	0.0000	0.1297	0.0177	7.3425	0.0000
$(1/r)dN^{CNC}$	-0.2871	0.3557	-0.8070	0.4197	-0.2986	0.3537	-0.8443	0.3985
$(1/r)dN^{CAD}$	-0.3702	0.3404	-1.0874	0.2769	-0.2635	0.2722	-0.9683	0.3329
CNC adoption after CAD	β_{CNC2}	σ_{CNC2}	*t test*	*P*				
Const	0.7130	0.1229	5.8016	0.0000				
CAD adoption after CNC	β_{CAD2}	σ_{CAD2}	*t test*	*P*				
Const	0.7113	0.0831	8.5618	0.0000				
Joint adoption of CNC & CAD	γ_0	σ_γ	*t test*	*P*				
Const	0.9793	0.1637	5.9821	0.0000				

Log likelihood: -10,207,454.4, n=6,739, # of parameters = 41.

Table 4: Complementarity effects: the role of plant-specific moderating factors

	CNC				CAD			
	β_{CNC}	σ_{CNC}	*t test*	*p*	β_{CAD}	σ_{CAD}	*t test*	*p*
Const	-2.0686	0.4488	-4.6088	0.0000	-1.4738	0.3949	-3.7318	0.0002
rp^{CNC}	-0.0354	0.0193	-1.8313	0.0671	-0.0532	0.0242	-2.1935	0.0283
dp^{CNC}	-0.3892	0.2970	-1.3106	0.1900	-0.1917	0.3438	-0.5576	0.5772
rp^{CAD}	-0.0024	0.0006	-3.8251	0.0001	-0.0042	0.0011	-3.8726	0.0001
dp^{CAD}	0.9514	0.4738	2.0082	0.0446	1.8760	0.5855	3.2042	0.0014
M	0.0004	0.0068	0.0618	0.9507	-0.0046	0.0056	-0.8274	0.4080
G	-0.0186	0.0356	-0.5216	0.6019	0.0274	0.0591	0.4638	0.6428
CR4	-0.0026	0.0018	-1.4337	0.1517	-0.0021	0.0018	-1.1834	0.2366
WR	-0.1803	0.2131	-0.8459	0.3976	-0.2474	0.1711	-1.4454	0.1484
S	0.0268	0.0098	2.7275	0.0064	0.0242	0.0131	1.8455	0.0650
NC	0.8345	0.0909	9.1784	0.0000	0.3786	0.1186	3.1922	0.0014
SC^{CNC}	-0.0180	0.0585	-0.3080	0.7581	-0.0624	0.0475	-1.3126	0.1893
SC^{CAD}	-0.0368	0.0473	-0.7782	0.4364	-0.0023	0.0430	-0.0527	0.9580
B^{CAD}	-0.0053	0.0158	-0.3342	0.7382	0.0484	0.0173	2.7933	0.0052
B^{CNC}	0.0969	0.0272	3.5598	0.0004	-0.0330	0.0319	-1.0342	0.3010
N^{CNC}	0.1446	0.0177	8.1717	0.0000	-0.0665	0.0173	-3.8487	0.0001
N^{CAD}	-0.1347	0.0213	-6.3360	0.0000	0.1327	0.0179	7.4196	0.0000
$(1/r)dN^{CNC}$	-0.3455	0.3566	-0.9690	0.3326	-0.2352	0.3537	-0.6649	0.5061
$(1/r)dN^{CAD}$	-0.3261	0.3426	-0.9519	0.3412	-0.2835	0.2741	-1.0344	0.3009

CNC adoption after CAD	β_{CNC2}	σ_{CNC2}	*t test*	*p*
Const	-1.3143	0.9459	-1.3894	0.1647
S	0.1017	0.0470	2.1627	0.0306
NC	0.2677	0.2723	0.9831	0.3255
B^{CAD}	0.0361	0.0598	0.6041	0.5458
B^{CNC}	0.0751	0.0825	0.9095	0.3631

CAD adoption after CNC	β_{CAD2}	σ_{CAD2}	*t test*	*p*
Const	0.3736	0.3167	1.1796	0.2382
S	-0.0045	0.0196	-0.2293	0.8186
NC	-0.4165	0.1771	-2.3520	0.0187
B^{CAD}	0.0614	0.0309	1.9845	0.0472
B^{CNC}	0.0576	0.0532	1.0827	0.2790

Joint adoption of CNC & CAD	γ_0	σ_γ	*t test*	*p*
Const	0.0970	0.9284	0.1045	0.9168
S	-0.0097	0.0431	-0.2258	0.8214
NC	0.6461	0.4401	1.4681	0.1421
B^{CAD}	0.0992	0.0885	1.1205	0.2625
B^{CNC}	0.1428	0.1222	1.1684	0.2426

Log likelihood: -10,169,071.2, n=6,739, # of parameters = 47.