Adoption of New Technology in a Two-level Supply Chain

Extended Abstract

by

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Introduction

We develop a model to analyze technology adoption in a supply chain. While the basic model is general, we are motivated by the case of RFID adoption in supply chains. We consider firms on two levels of the supply chain: supplier firms and buyer firms. Industry experience with RFID adoption suggests that some firms, especially on the supply side, have a great amount of uncertainty in estimating the benefits of RFID adoption. This uncertainty is reduced as other supplier firms adopt RFID and information from their experiences becomes available. In addition, the benefit a supplier firm may see by adopting RFID is dependent on the number of its buyers who have already adopted. Thus, at any given time, the estimate of benefit for a supplier depends on the number of supplier firms and number of buyer firms who have already adopted the technology. We seek to capture this dependence and analyze its effect on the adoption of a new technology like RFID.

Our model follows a stream of technology adoption literature and makes a contribution to it. McCardle (1985) considered the technology adoption decision for a firm using a dynamic model where, in each period, information can be purchased to update the estimate of adoption benefit. Ulu and Smith (2009) recently extended that model to consider general probability distributions for benefit and general information signals. Chatterjee and Eliashberg (1990) presented a model to explicitly capture the effect of uncertainty on the firm’s utility and to aggregate individual firms’ decisions to produce a diffusion curve. Another related paper is Whang (2010). None of these papers consider the effect of other adoptee firms on the availability of information signals. The impact of buyer firms’ adoption decisions on the supplier firm’s benefits is also new to this literature. In the following, we briefly discuss a firms’ decision model, our analytical results, and the extension to a population model. We very briefly describe an empirical study to test insights generated from the analytical model.

Model and Results

We first focus on an individual supplier firm’s adoption decision and then develop a population model. The firm’s prior belief about the per-period benefit of adopting the technology is normally distributed. The total per-period benefit for the firm is linear in the number of its buyers (exogenously given) who have already adopted the technology. The firm is risk averse. We put
these elements together to specify a per-period utility function for the firm. The cost of adoption is modeled as a one-time fixed cost.

At the end of each period, the firm observes an information signal which is generated based on the number of other supplier firms who adopted the technology in the previous period. In the individual firm’s model, this number is assumed to be exogenously given; the assumption is relaxed in the population model later. Each of these other suppliers experience a benefit realization drawn from the true distribution of the benefit (assumed normal with unknown mean and a specified standard deviation). The firm uses this signal to develop a posterior distribution of the benefit which is also normally distributed.

We can now model the firm’s adoption decision as a dynamic program. The state space in each period includes the firm’s prior belief distribution (which depends on number of supplier firms that have already adopted) and number of buyer firms that have already adopted the technology. As more firms adopt, their information reduces the standard deviation of the firm’s prior distribution of benefit and that, in turn, increases the firm’s per-period utility. The action space includes adoption or no-adoption in this period. Using a discount factor, we can specify a finite-horizon dynamic formulation. To keep the presentation brief, we discuss a two-period formulation here.

To be more specific about the two-period (T=2, t=1,2) model, let us consider an individual supplier firm. It has a belief about the benefit $p_t$ that it will derive from adopting the technology and servicing one buyer in one period. The real value of this benefit follows a normal distribution that has a mean unknown to the firm and a known variance $\sigma^2$. At the beginning of period $t$, the firm’s belief about the unknown mean is normally distributed with $\mu_t$ and variance $s_t^2$. The firm’s benefit from an adoption in time period $t$ are given by $B_t = m_t p_t$, where $m_t$ is the number of buyers who have already adopted until period $t$. Using $a$ to represent the firm’s risk aversion index, its per-period utility for adoption is given by $u_t = 1 - e^{-am_t p_t}$ and $U_t = E[u_t] = 1 - e^{-am_t \mu_t + a^2 m_t^2 (\sigma^2 + s_t^2) / 2}$. The firm’s adoption decision in the last period $T$ is made by comparing $U_T + \delta V_T$ with $K$ where $K$ is the fixed cost of adoption, $V_T$ is the terminal value and $\delta$ is the discount rate.
At the beginning of period $T$, the firm arrives at its posterior distribution $N(\mu_T, s_T^2)$ after updating its prior $N(\mu_{T-1}, s_{T-1}^2)$ at the end of period $T-1$. It does so by observing $q_{T-1}$ firms that adopted in previous period $T-1$ and their benefit observations $X_1, ..., X_{q_{T-1}}$, drawn from a normal distribution with an unknown mean and known variance:

$$\mu_T = \frac{\mu_{T-1} + \sum_{i=1}^{q_{T-1}} X_i (s_{T-1}^2 / \sigma^2)}{1 + q_{T-1} (s_{T-1}^2 / \sigma^2)}, \quad s_T^2 = \frac{s_{T-1}^2}{1 + q_{T-1} (s_{T-1}^2 / \sigma^2)}.$$

At the beginning of period $T-1$, the firm sets up a similar adoption decision. Now, however, the firm must estimate $\tilde{q}_{T-1}$, and $\tilde{m}_{T-1}$ the number of other supplier firms and buyer firms, respectively, that may adopt in period $T-1$. We assume that $\tilde{m}_{T-1}$ is exogenously prescribed but $\tilde{q}_{T-1}$ depends on a population model of supplier firm that is discussed below. We then use these estimations to develop $U_{T-1,T}$, the firm’s expectation of utility it will derive in period $T$. We explicitly describe $U_{T-1,T}$ and use it to build a decision rule for making adoption decision at the beginning of period $T-1$.

Our analytical results show that the firm will adopt if a function of number of supplier and buyer adoptee firms is more than a threshold value. That is, a firm’s adoption decision is made based on a state-dependent threshold. We then prove results about how this threshold changes as a function of the risk-aversion index of the firm. We also show the effect of the mean and standard deviation of the prior at time zero on the threshold.

Our next step is to embed the firm-level adoption model into a population model. To begin with, we model the population of supplier firms as heterogeneous in risk-aversion and identical in all other respects. We also assume that each supplier serves all buyers. We show that, in each period, there exists a critical level of risk-aversion index such that all firms at or below that level will adopt the technology and all firms above that level will not adopt and chose to wait. The main challenge here is to find equilibrium between a firm’s estimate $\tilde{q}_{T-1}$ of how many other firms will adopt and the number of firms $q_{T-1}$ in a given population that will actually adopt. We prove that such equilibrium $\hat{q}_{T-1}$ exists and is unique.

Defining such equilibrium allows us to derive an adoption curve that is specified by the accumulated fraction of firms that have adopted the technology in or before any given period.
We show how to compare any two adoption curves so that one can be called to represent faster adoption than the other.

We now consider the effect of several strategies observed in practice. First, RFID adoption is characterized in practice by some large retailers (buyers) adopting the technology and then mandating supplier firms to adopt it. We capture this in our model by various combinations of number of buyer and seller firms that have adopted at time zero or at an early time. We provide insights into what particular combinations and timing of mandated adoption will be more effective in achieving a faster adoption curve. Second, many firms invest in RFID pilot programs to get a better estimation of the benefit. We model this by introducing another possible action for the firm; a reduction in the standard deviation of the prior can be obtained at a fixed cost. We discuss conditions under which such an action is useful for the firm.

We extend the model in several directions. We consider the case where there is a cost for observing information and the possibility that the information is not truthful. We include other types of heterogeneity - mean and standard deviation of the prior - in the population. Numerical experiments yield other managerial implications.

**Empirical Study**

Our analytical model assumes that each supplier firm in the population is connected to all the buyer firms; in reality the specific nature of the network of linkages between supplier and buyers will influence the adoption curve. In addition, the strength of connections (tie strength) between supplier firms will influence the quantity and quality of information transmission between supplier firms. We collected data about RFID adoptions over a period of two years and gathered information to build a network of linkages between these firms. We consider tie strength to be a function of the following two parameters: geographical proximity and industry relatedness. Based on our data, we derive measure for both these parameters and develop an estimate of tie-strength between pair of firms in our population. We divide the horizon into discrete periods and develop the notion of cumulative tie strengths over time. The firm continuously receives and observes prior adopters’ information in each period until the firm adopts. To reflect this in cumulative tie strengths, total strength of ties coming to firm j is updated by all ties coming from
prior adopters in earlier periods and any new additional ties coming from new adopters in the just-completed period.

Drawing upon the idea of an adoption threshold from our analytical model, we next develop an adoption timing model that includes both: various firm attributes and its tie strength. To examine the determinants of the likelihood and timing of the technology adoption, we estimate various hazard models and the tobit model. Duration modeling views the adoption as the hazard and therefore allows us to determine simultaneously the factors that influence both the probability and rate of adoption. Tobit model relies on cross-sectional data from the last period for the variables and provides a supplement to the results of the duration model. We use this empirical model to test the impact of firm attributes and tie strengths on adoption timing decisions.

We find that firms with more subsidiaries and lower type of risk adopt RFID earlier than others. The main finding is that the social proximity plays a critical role in the adoption of technology. That is, a firm can gain access to other firms’ information and knowledge about new technologies by interactions through ties in networks. We argue that structural relationships such as social ties among firms affect the rate and extent of adoption and diffusion.

**References**


