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Expectations, network effects and timing of technology adoption: some empirical evidence from a sample of SMEs in Italy

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Abstract We provide evidence on the influence of expectations and network effects on the timing of technological adoption. By considering a sample of SMEs operating in Italy, we focus on the determinants of their decision to adopt Fast Ethernet, a communication standard for Local Area Networks (LANs). We find that both expectations and network effects significantly affect the timing of adoption. In particular, price expectations generally tend to delay adoption and (indirect) network effects in the form of backward compatibility as well as informational spillovers tend to foster adoption. Firm size also matters.

Keywords Diffusion · Network Effects · Expectations · LAN equipment

JEL Classifications O33 · L63 · L26

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1 Introduction

A large body of both theoretical and empirical literature deals with the issue of innovation diffusion. Theoretical models offer predictions on the characteristics of early and late adopters who are expected to adopt. Empirical studies test these predictions. Most of the empirical studies tend to focus on the determinants of diffusion, by actually providing evidence on the *probability to adopt*. A few empirical studies instead analyse the factors affecting the *timing of adoption*. Although concerned with similar issues, these two categories of studies differ in the object under investigation, since the first one investigates variables affecting the decision to (or not to) adopt as such, while the second one examines factors influencing the speed of adoption. The present work follows the tradition of the second group of studies and analyses the determinants of the timing of adoption.

Among the most important factors affecting timing of adoption there are price and technological expectations as well as network effects. Expected improvements in the innovation and/or the likelihood that it will experience improvements in the near future contribute to postpone adoption (Balcer and Lippman 1984). Beside expectations, timing of adoption is also likely to be influenced by network effects (Church and Gandal 2004). In the presence of network effects, the utility from adoption increases in the number of other adopters that purchase the innovation.

Interdependence among adopters is a powerful source of positive feedbacks for adopters who must decide when to adopt, taking into account both the current network size and its perspectives for future growth. There is little empirical evidence on the impact of expectations on adoption, the only work being that of Weiss (1994), which provides empirical support to the hypothesis that technological expectations delay adoption. Many empirical studies look instead at the impact of the presence of network effects on timing of adoption. These studies generally rely on indirect measures of network effects such as network size (Dranove and Gandal 2003; Gandal et al. 2000), or employ duration models to estimate the probability of transition from a non adopter to an adopter status (Saloner and Shepard 1995).

This paper provides empirical evidence on the impact of expectations and network effects on speed of adoption. In particular, it considers the case of the adoption of Fast Ethernet, a high speed standard for Local Area Networks (LANs), which constitutes a technological upgrading with respect to a previous version of the standard called Ethernet. The data used in this paper come from a survey of 128 small and medium size enterprises operating in Italy that have a LAN in place. The survey was carried out in December 2003 and was intended to investigate the impact of expectations and network effects on the speed of LAN upgrading from the standard in place (Ethernet) to a faster though compatible standard (Fast Ethernet). The cross section provides information on when Fast Ethernet was adopted, the characteristics of the respondent firms such as size and type of activity, as well as information on the determinants of their adoption choices in general and with specific regard to the decision to upgrade their network.

The econometric estimation enables us to study the determinants of differences of behaviour across the surveyed firms categorised with respect to when they first adopted Fast Ethernet (i.e. pioneers, early adopters, laggards). In particular, we address the following question: how did expectations and network effects influence the differentials in timing of Fast Ethernet adoption across the firms in our sample? Particular attention is devoted to the identification of the role played by different mechanisms underling network effects. We are able to directly measure the influence of different types of network effects on adoption behaviour and assess the way they impact on timing of adoption, while controlling for sample selection bias.

The structure of the paper is as follows. Next section reviews the existing empirical and theoretical contributions on expectations and network externalities as determinants of timing of technology adoption. Section 3 provides the background on the LAN technology and industry to put the case of Fast Ethernet adoption in context. Section 4 describes the sample and the structure of our survey. Section 5 presents the empirical models and the results. Conclusions and limitations of the paper are discussed in Sect. 6.

2 Expectations, network effects and timing of adoption: a literature review

What influences the timing of adoption of a new technology? In this section we will consider how existing contributions have addressed this issue, by looking in detail at the main results from the literature, which are of interest to our specific case, (i.e. timing of adoption of a superior technological standard in the LAN industry). The existing literature on innovation draws different conclusions on the factors affecting the speed of adoption, on the basis of the assumptions and the viewpoint taken by each specific model. Equilibrium models for instance, consider the case of *heterogeneous* potential adopters who are informed on the existence of the technology and evaluate the opportunity of adoption by comparing gross benefits, and costs from the acquisition.[1] The individual timing of adoption depends on how gross benefits and adoption costs are distributed across potential adopters and contributions vary according to the attention placed on specific factors affecting these costs and benefits, and their rate of change, which differ substantially across potential adopters.

In this context, it is possible to distinguish between *rank models* that are based on the size dimension and consider individual characteristics as independent, excluding the possibility of influence from early adopters to non-adopters, and *game theoretic* (stock and order effect) models, that consider the strategic

[1] Several surveys of equilibrium diffusion models exist in the literature (Stoneman 1983; Dosi 1991). For this short review, we follow Stoneman (2002).

interaction between firms (Karshenas and Stoneman 1993; Stoneman and Kwon 1994). Here, the existence of strategic behaviour makes firms' heterogeneity irrelevant for the generation of diffusion paths and, under some conditions, identical firms may adopt the innovation at different dates. *Order effect* models assume that the firm's position in the adoption sequence determines its gross return from adoption and state that early adopters obtain the greatest returns from the adoption and enjoy some sort of first mover advantage. *Stock effect* models assume that, as the number (stock) of users increases, the gross benefits from adoption decline. For any given level of costs of acquisition there are a number of adopters beyond which adoption is not profitable. The underlying mechanism is that the cost of acquisition of the new technology falls over time and further adoption occurs. The acquisition of new technologies lowers the production costs and this leads to changes in the output and in the prices of the industry as a whole, with a consequent effect on the profitability of further adoption.

Within this theoretical set up, empirical studies focus on the probability of a firm having adopted an innovation by a given time and, more interesting for the present work, on the timing of technology adoption. Low acquisition costs and/or a decrease in such costs tend to increase adoption probability (Stoneman and Ireland 1983; David and Olsen 1986). Firm size increases the probability too, either by increasing the extent of returns from innovation (David 1969), or by improving returns to scale (Davies 1979). Furthermore, firms that perform more R&D are highly receptive to a new technology and have a higher probability to adopt than those that carry out less R&D (Cohen and Levinthal 1989). The speed of adoption is affected by less time invariant factors, such as price and technological expectations, and network effects. These seem to be particularly important when considering the speed of adoption of a superior standard in the case of networking technologies.

The paramount role of expectations in influencing timing of adoption has been explicitly recognised since the seminal contribution of Rosenberg (1976). Potential adopters may delay adoption if they expect the price of innovation to decline in the near future. Moreover, waiting for 'bugs to be fixed', prototypes to be refined and more in general technical improvements to occur can be another important source of delay. These intuitions have been successfully confirmed and incorporated into formal models of adoption (Balcer and Lippman 1984). Empirical evidence on the effects of expectations on timing of adoption is rather scarce. Weiss (1994) empirically tests the predictions of the model of Balcer and Lippman on a sample of firms considering the adoption of surface mount technology, a process innovation for assembling circuit boards. He finds that technological expectations in the form of greater expected improvements tend to delay adoption and contribute to stall the diffusion of this specific process innovation.

Timing of adoption may also depend on the technology to be used alongside another technology and/or the adopter becoming part of a network of users. This is particularly important for the case of adoption/upgrading of technological standards for communications network such as LANs. Two types of networks are generally identified in the literature: direct and indirect networks. Direct networks arise when adopters become part of a network by purchasing a product that provides a (direct) connection between the adopter and other users who bought the same product. Being able to interact directly with other users is the main source of utility adopters can gain from adopting. Typical examples of direct networks are the telephone exchange and the fax. In the case of indirect networks, adopters gain utility from the joint consumption of two components that interact to form a system. In this case, the product (hardware component) has no direct value for the adopter unless it is used in combination with another product (software component); here vertical compatibility (between the system components) matters. Examples of indirect network can be found in the field of computing (operating systems and application software) and consumer electronics (video cassette systems, compact disks).

Both network types are characterised by the presence of a *network effect*. A network effect exists "if the value [of adopting a system component] increases in the number of other adopters that (ultimately) join the network by purchasing compatible products" (Church and Gandal 2004; p. 4). The *source* of benefits from the network effect is the same in both types of network and positively depends on the size of the network when adoption occurs.

The larger the network, the greater are the benefits from adoption. However, the *mechanisms* of transmission of the benefits vary according to the type of network.

In the case of direct network effect, network size approximates the adopter's desire for horizontal compatibility. Having a large network of compatible mobile phone users for instance makes new users more likely to join. When the network effect is indirect, network size can be in the first place a proxy for the availability of complementary components of the technical system. In this case network effects are *physical* in the sense that they require compatibility between the hardware and the software components of the system to operate. The physical network effect is particularly strong when adopters' desire for vertical compatibility and/or variety is high. To the extent that the hardware component is compatible with a wide range of software components, a larger installed base of hardware is an indication of higher benefits for adopters who have a strong preference for variety. System components may undergo technical change. However, as long as backward compatibility is maintained, the network effect ensures that utility from the consumption increases. As we will argue in the next section, this is what happened when Fast Ethernet was introduced in the LAN industry.

Besides being a proxy for desire of horizontal and/or vertical compatibility, network size is also an indicator of the past behaviour of existing users and manufacturers. At a specific point in time, network size conveys to potential adopters information about the characteristics of the technology and the payoff from its adoption, which help firms to make inference on the opportunity to adopt it. In this case network effects are *virtual* and can be understood as a particular mechanism for conveying learning spillovers. Physical and virtual effects may be combined, as in the model by Choi (1997). Within this context, Choi shows that the combination of virtual and physical effects may have ambiguous effects on the timing of adoption of a new technology. On the one hand, informational spillovers from previous adopters encourage further adoption by those who prefer to imitate to avoid the risk of choosing an alternative with a lower payoff. On the other hand spillovers may be a source of inertia. If early adopters are aware of being a source of spillovers, they may delay adoption to avoid the risk of being stranded if, by choosing the other alternative, followers end up enjoying a higher payoff than the known one.

Empirical studies of network effects and diffusion generally fall within two main categories. In the first category there are aggregate (industry) level studies. These studies typically confirm that the presence of network effects foster technology diffusion. They usually rely on network size as an indicator of the existence of network effects. As a consequence, they are generally incapable of singling out the effect of different mechanisms underlying the two types of network effects. Neither do they explicitly address the issue of the determinants of the timing of adoption at the individual firm level.

More interesting for the scope of this paper is the second category: *micro (firm) level studies*. These contributions employ a variety of econometric approaches to investigate network effects as determinants either of the speed of diffusion, or of the choice among alternative technologies at the individual firm level. Saloner and Shepard (1995) employ duration models to study the speed of diffusion of ATM on a sample of banks in US. They find that banks with many branches, a proxy for the (indirect) network effect, generally adopt ATM machines earlier than banks with fewer branches. Gowrisankaran and Stavins (2004) study the role of network effects in influencing the adoption of automated clearing houses payment systems by a sample of US banks. They find that adoption is positively influenced by the number of banks who have adopted the same technology (direct network effect) as well as, although to a lesser extent, by the number of users of the payment system (indirect virtual effect). Augereau (1999) analyses the adoption of 56K modems by ISPs in US. She finds that, controlling for firms' heterogeneity, the probability to adopt a certain type of modem increases in the market share of the modem type, therefore providing support for the presence of (indirect) network effects. Finally, Goolsbee and Klenow (2002) consider the diffusion of personal computers across US households. They find a positive relationship between the probability to adopt and the (mean) number of adopters in the same metropolitan area. When trying to assess the contribution of different sources of network effects on this result, they find that these positive effects are more likely to be explained by learning spillovers (i.e. virtual effects) rather than by the use of specific software or by other local effects such as local prices and/or peer pressure. A summary of selected contributions for both categories of studies is reported in Table 1 below.[2]

This paper takes a micro level approach to study the impact of expectations and network effects on adoption. It considers a cross section of SMEs and identifies several proxies of network effects in order to be able to disentangle the impact of direct and indirect network effects. In the next section we provide a description of the LAN industry and technology and we identify why network effects and expectations are important determinants of the decision to adopt.

3 Background on the LAN industry and technology

LANs are technical systems that form the infrastructure connecting PCs, workstations and peripherals across a single or several company sites within an area of relatively small dimensions. Being technical systems, LANs are made up of different hardware pieces (i.e. adapter cards, hubs, switches and routers), each of them carrying out a specific function for the purpose of exchanging data. The rules and the speed at which data are exchanged are defined by communication standards (i.e. Ethernet, Token Ring, and Fast Ethernet). LANs started diffusing in firm environments from mid-1970s and since then several standards have characterised the evolution of the technology during different phases (Christensen et al. 1995). During the 1980s Ethernet became the dominant standard (von Burg 2001). As a high speed upgrade to Ethernet, Fast Ethernet was officially standardised in 1993 and became the dominant high speed LAN standard between 1995 and 1998. Fast Ethernet was first implemented in hub equipment but its diffusion received a significant boost with the arrival of switches which currently continue to support the growth, while hubs have become obsolete. This paper analyses the determinants of the speed of Fast Ethernet diffusion, by concentrating on the determinants of technological upgrading. In particular, we focus on three factors: (indirect) network effects, expectations and switching costs.

Indirect network effects are important because, to become viable, Fast Ethernet requires to be embedded in components of the 'enabling LAN infrastructure', such as hubs and switches. Being 'physically' compatible with Ethernet makes Fast Ethernet appealing for buyers with Ethernet in place and attracts high support from manufacturers of both hubs and switches. Wide component availability in turn triggers fast price decline and contributes to make the standard popular. Alongside physical indirect effect, learning effects can also influence adoption. Although Fast Ethernet is a non proprietary standard, its implementation (i.e. setting-up and connection) and management (i.e. configuration and troubleshooting) are carried out by specific software packages. These packages are 'vendor specific' and sometimes incompatible across manufacturers. Learning how to use the software to perform these activities takes time and requires training. Forman and Chen (2006) provide evidence on the impact of learning on LAN equipment adoption. In particular they find that, after learning how to use software from a specific manufacturer, firms become more likely to continue purchasing equipment from the same manufacturer rather than to switch and incur the costs of retraining. Previous use of vendor specific software generates a powerful network effect that can affect adoption. Rather than deriving from physical compatibility, this effect depends on previous learning. It is, so to speak, 'virtual' in the sense defined in Sect. 2 above.

Price and technological expectations also affect the decision to adopt Fast Ethernet. The arrival of switches has been accompanied by a dramatic fall in equipment prices. Expectations of further price decline may induce firms that have not yet adopted to further defer adoption. Moreover, today Fast Ethernet is a mature and established standard. Its characteristics are known and the technology fully developed. The existence of another alternative (Gigabit Ethernet) in competition with Fast Ethernet can affect the decision to adopt. Gigabit Ethernet is the third generation upgrade to Ethernet. It is backward compatible with both Ethernet and Fast Ethernet and runs at 1,000 Mbps a hundredfold

[2] Empirical research on network effects has been growing over the last decade. The table highlights only a selection of empirical contributions and the indicators that have been used as proxies for the network effect. It does not aim at being exhaustive.

Table 1 Summary of selected empirical studies of network effects

		Type of study					
		Industry level			Firm level		
		Reference	Industry	Type and proxies of network effect	Reference	Industry	Type and proxies of network effect
Type of network effect	Direct	Economides and Himmelberg (1995)	Fax machines, US (1978–1991)	Virtual	Goolsbee and Klenow (2002)	Home computers (1997)	Virtual
			Annual data	Lagged installed base			Internet and email use
		Gandal (1994)	Spreadsheet (1986–1991)	Physical	Gowrisankaran and Stavins (2004)	Automated payment systems (1995–1997)	Physical and virtual
				Lotus compatibility (dummy)			No of previous adopters
				External database compatibility (dummy)			
				LAN compatibility (dummy)			
	Indirect	Dranove and Gandal (2003)	DVD vs. DIVX standards (1997–2000)	Physical and virtual	Saloner and Shepard (1995)	ATM (1972–1979)	Physical
			Monthly data	Software availability (Log of impact measure)			No of branches
				Dummy for pre-announcement			
		Gandal et al. (2000)	CD Players (1985–1992)	Physical	Augereau (1999)	56K Modems (1997)	Physical
			Quarterly Data	Installed Base of CD players (Log)			Market share of modem type
				Compact Disks Availability (Log)			
		Koski (1999)	Operating systems (Apple MS-DOS) and Microcomputers (1985–1994)	Physical			
			8 European countries	Installed Base Sales of operating systems			
			Annual Data				

increase in speed with respect to Ethernet (Cheng et al. 2005). Gigabit Ethernet is now fully available in the market, but its commercialisation had just started when our survey was conducted. For those firms that had not yet upgraded their LANs, Gigabit Ethernet could represent an alternative to Fast Ethernet. Expectations of its availability could have influenced the timing of upgrade.

Finally switching costs matter because buyers of LAN standards typically need to make physical changes to their LAN architecture. Adopting a standard may require firms to change existing facilities such as existing wiring and cabling (i.e. from copper wire to fibre), move computers, and reconfiguring existing portions of the network. High switching costs are typically associated to slower adoption.

The variables intended to capture these effects will be presented in Sect. 5. Next section will present the sample and explain how the survey was carried out.

4 Sample description and descriptive evidence

The analysis in this paper focuses on a sample of SMEs in Italy. In particular, it relies on a survey of 128 SMEs that have a LAN in place. These firms operate in the computing service industry (NACE 72). The sample was chosen from the AIDA Dataset that contains balance sheet information on firms operating in Italy. We selected firms in the computing service industry, since we believe that high-tech firms should be more inclined to use new technologies. In December 2003, telephone interviews were carried out with the purpose of understanding what were the standards and the type of equipment in place, as well as of identifying the factors affecting the decision to adopt new ones.

For the survey methodology we followed the ‘key informant’ methodology described in Weiss (1994) aimed at interviewing those people who have a key role in all decision making processes related to LAN equipment. In particular, interviews were specifically targeted to the personnel in charge of the firm IT budget such as Chief Information Officers or, being the sample made of SMEs, network and/or telecommunications managers. We collected 98 completed questionnaires, which gave us a fairly high response rate (77%).

The survey is made of 25 questions and structured in four sections. Section A aims at collecting general information about firms in terms of sector, location, size and revenues. Section B focuses on the technological endowment of firms—in terms of network type (Internetwork, LAN, WAN), number of nodes, type of equipment (i.e. hubs and switches) as well as applications (i.e. client server, email, intranet etc.) in place—and on the costs of acquiring and upgrading the network in terms of human resources and physical investments. Section C analyses objectives, drivers and obstacles to technology adoption, as well as the expectations of firms in terms of price and technological improvements. Section D examines the characteristics of adoption processes, also in relation to the existence of network effects and to the features of the market.

A specific question in the survey asked respondents to report how many months before the survey they first adopted each equipment and standard currently deployed in their network. Four different options were given: a) Less than 12 months before being surveyed, b) Between 12 and 18 months, c) Between 19 and 24 months, d) More than 24 months. Table 2 reports the number of adopters by standard and timing of first adoption.

As expected, the most common standards are Ethernet and Fast Ethernet, adopted by 87% and 76% of firms in our sample. Token Ring (24%), a low speed standard competing with Ethernet, is less adopted. Table 3 reports information on the characteristics of the firms in our sample.

Overall these figures confirm that the majority of firms in our sample are SMEs (73% of respondents have less than 500 employees) with small LANs in place (82% of firms have less than 100 nodes connected). Although all firms are located in Italy, the majority of them (56%) have an international profile (i.e. they are subsidiaries or units of

Table 2 Pattern of LAN standard adoption (no of firms)

	<12	12–18	18–24	>24	% of adopters
Ethernet	4	21	35	25	87
Fast Ethernet	7	12	32	24	76
Token ring	3	7	12	2	24
FDDI	1	2	7	2	12
ATM	0	0	2	0	2

Table 3 Pattern of Ethernet and Fast Ethernet adoption by firm characteristics

	Sample (%)	Ethernet				Fast Ethernet			
		<12 (%)	12–18 (%)	18–24 (%)	>24 (%)	<12 (%)	12–18 (%)	18–24 (%)	>24 (%)
Firm type									
National	41	2	7	14	15	3	2	10	12
International	56	2	14	20	10	3	10	20	12
Local	1	–	–	–	–	–	–	1	–
Regional	2	–	–	1	–	1	–	1	–
No of Employees									
<500	73	3	15	24	21	6	7	24	17
500–999	20	1	6	7	1	1	5	5	3
1000–5000	7	–	–	4	3	–	–	3	4
Revenues (euros)									
100K–499K	9	–	1	3	2	1	–	4	3
500K–999K	33	2	6	13	9	2	3	5	7
1M–10M	41	2	11	10	10	2	5	18	10
>10M	17	–	3	9	4	2	4	5	4
Type of network									
Internetwork	26	1	3	12	7	–	2	8	6
LAN	58	3	17	15	12	6	9	18	14
WAN	16	–	1	8	6	1	1	6	4
No of nodes									
<50	50	3	9	18	18	4	5	18	14
50–100	27	1	9	11	3	2	3	9	5
101–250	10	–	3	3	3	1	3	1	3
251–500	5	–	–	3	–	–	1	2	1
>500	3	–	–	–	1	–	–	2	1

multinational corporations). From Table 3 we can also gain preliminary insights on the relationship between firms' characteristics and the pattern of Ethernet and Fast Ethernet adoption. The majority of Ethernet and Fast Ethernet adoption occurred between 18 and 24 months before the survey took place irrespectively from firms' characteristics. As argued in the previous section Ethernet and Fast Ethernet are the most common standards in the LAN environment. Moreover, both standards have been in the market for a while, so that it is not surprising that they were adopted relatively early.[3]

[3] Additional information reveals that client server applications (81%), intranet and extranet developments (30% and 32% respectively), and emails (22%) were the most important drivers of firms' decision to adopt new LAN standards and equipment.

In the present paper, we are interested in investigating whether there is a relationship between Fast Ethernet adoption and previous use of Ethernet, in particular if having adopted Ethernet affected the timing of Fast Ethernet adoption, which would support the idea that physical network effects play a role in determining the speed of technological upgrading. In the next section we will explore this possibility.

5 The empirical analysis of Fast Ethernet adoption

In this section, we take a micro level perspective to study the factors affecting the timing of Fast Ethernet adoption. As argued in the previous section, 76% of the firms in our sample adopted Fast Ethernet. A slight majority of them (52%) adopted Fast Ethernet after Ethernet. Given the high compatibility between Ethernet and Fast Ethernet, it could be expected these firms to prefer Fast Ethernet to the alternatives as high speed upgrade for their LANs. However, 47 (48%) firms in our sample behaved differently. Twenty four firms adopted Fast Ethernet before adopting Ethernet. These firms had another low speed technology in place (i.e. Token Ring). Twenty three firms had not adopted Fast Ethernet when the survey was carried out, although they had Ethernet in place. In this section we investigate the determinants of this heterogeneity. In particular, we address the following question: how did expectations and network effects influence the differentials in the timing of Fast Ethernet adoption across firms in our sample?[4]

5.1 The model

In order to answer our research question, we use information on firms that were current users of Fast Ethernet at the time the survey was carried out. To these firms we can assign a specific status according to the timing of their adoption of Fast Ethernet. In particular, we classify firms as *Pioneers* (those that adopted Fast Ethernet before Ethernet), *Early adopters* (those that adopted Fast Ethernet within 12 months from the first adoption of Ethernet), *Laggards* (those that took more than 12 months to upgrade from Ethernet to Fast Ethernet), *Non adopters* (those that have adopted Ethernet, but not yet upgraded to Fast Ethernet).[5] On the basis of this classification we create a variable $Status_j$ that takes the value of ($Status_0 = 0$) if the firm is a *Pioneer*, ($Status_1 = 1$) if the firm is an *Early adopter*, ($Status_2 = 2$) if the firm is a *Laggard*. *Status* is inherently ordered according to the timing of Fast Ethernet adoption.[6] *Non adopters* are not current users of Fast Ethernet and should not be included in the same group as *Pioneers*, *Early adopters* and *Laggards*. However, using only information on the sub-sample of adopters may introduce a sample selection bias. To eliminate the potential source of misspecification, we opt for a two-step estimation model similar to Heckman procedure for selection bias (Heckman 1979). In the first step, we use a binary response model to explain the probability of adopting Fast Ethernet as a function of a series of independent variables. In the second step, we focus only on current users to look at the determinants of the timing of adoption, as summarised by the variable $Status_j$, and correct for selection bias. Several papers in the literature have been employing this procedure. Our presentation of the model draws heaviliy on Dimara and Skuras (2001).

Let us call $Status_j^*$ the latent variable associated to the ordered variable $Status_j$:

$$Status_j^* = Z_j'\gamma + \eta_j, \tag{1}$$

where Z contains the explanatory variables, γ are the coefficients to be estimated, and η is a random error term. $Status_j^*$ is not observed. We observe instead intervals in the realisation of $Status_j^*$:

$$\begin{array}{llllll} Status_0 = 0 & if & Adopt = 1 & and & Status_j^* \leq \mu_1 \\ Status_1 = 1 & if & Adopt = 1 & and & \mu_1 < Status_j^* \leq \mu_2 \\ Status_2 = 2 & if & Adopt = 1 & and & \mu_2 < Status_j^* \end{array} \tag{2}$$

where μ are, usually unknown, parameters to be estimated with γ. The probabilities that respondents firms belong to one of these intervals can be estimated only for that part of the sample in which the firm is actually an adopter of Fast Ethernet. Not accounting for this would lead to a possible selection bias of the estimation. To correct for this problem, we follow the procedure by Heckman (1979), who

[4] We are aware of the importance of investigating the overall attitude of firms towards technological innovations and the strategy they follow in their adoption choices with respect to LAN standards, when analysing the process of adoption of new technologies. A thorough analysis of these issues goes beyond the scope of this paper, but constitutes the object of a research we are currently carrying out (see Corrocher and Fontana 2006).

[5] We are specifically interested in the timing of adoption of Fast Ethernet, and not in the process of adoption of high speed standards in general. Therefore, we consider adopters of FDDI and ATM as non adopters.

[6] This classification is clearly inspired by Rogers (2003), who identifies five 'ideal types' of adopters (Innovators, Early adopters, Early majority, Late majority and Laggards). However, while Roger's distinction is done on the basis of sociological and behavioural attitudes toward innovation, our distinction is not driven by the same concerns.

suggests a two stage procedure that relies on a first estimation of a selection equation for the entire sample of firms.

Let us call $Adopt_j$ a binary variable describing whether a firm i is an adopter of Fast Ethernet. A latent variable $Adopt_j^*$ is associated to this binary variable:

$$Adopt_j^* = X_j\beta + \varepsilon_j \tag{3}$$

in which X is a set of explanatory variables, β are the coefficients to be estimated, and ε is a random error term. The parameter β can be estimated by replacing $Adopt_j^*$ with a dummy variable $Adopt_j$. When $Adopt_j$ equals zero, a firm does not adopt (i.e. $Adopt_j^*$ is zero or negative). When $Adopt_j$ equals one, the firm is an adopter of Fast Ethernet (i.e. $Adopt_j^*$ is positive). In this case the selection equation can be treated as a binary probit model and estimated by maximum likelihood $\left(\hat{\beta}\right)$. For all the firms in our sample we can estimate the probability to adopt Pr($Adopt_j$ = 1) that can be computed as $\Phi\left(X_j'\hat{\beta}\right)$ where σ is the cumulative distribution function of a standard normal. In the second stage we estimate a regression model augmented by the selection variable $\hat{\lambda}_j = \varphi\left(X_j'\hat{\beta}\right)/\Phi\left(X_j'\hat{\beta}\right)$ where φ $(\cdot\ )$ is the standard normal density function restricted to those firms who have adopted. In other words we estimate the following:

$$Status_j^* = Z_j'\gamma + \gamma_\lambda\hat{\lambda}_j + \eta_j \tag{4}$$

for all j with $Adopt_j^* > 0$.

Several contributions implement an ordered probit regression in the second stage (Demoussis and Giannakopulos 2006; Poon 2003; Mohen and Horeau 2003; Dimara and Skuras 2001). The ordered probit model is particularly suitable for estimation when the dependent variable is discrete and ordinal in nature, which is our case. However, the ordered probit model assumes that the thresholds μ_j are unknown and have to be estimated together with the coefficients from the regression. In our case, the thresholds are known. Indeed, our dependent variable $Status_j$ is 'interval coded' in the sense that it is the result of the grouping of a continuous variable into known intervals whose extremes are the timing of adoption defined in months. The ordered probit estimation can be modified in such a way to fix the thresholds at their known values and to estimate only the coefficients and error variables.[7] This estimation is called 'interval regression' and employs maximum likelihood techniques.[8]

Table 4 Definition of the dependent variable for the Interval regression model

Status	Associated interval	Lower	Upper	Frequency
0	$(-\infty, 0]$	.	0	24
1	(0, 12]	0	12	37
2	$(12, +\infty]$	12	.	14

To estimate interval regressions, the ordinal categorical dependent variable has to be recoded into two variables (Lower and Upper) each of which defines an endpoint of the interval. Table 4 shows the concordance.

Estimated coefficients from interval regressions can be interpreted as if $Status_j^*$ can be observed for each firm j and estimated by OLS. In other words, coefficients can be interpreted as marginal effects (i.e. changes in the dependent variable following a change in a specific independent variable *ceteris paribus*). Our data are both left and right censored, so the lower and upper endpoint are represented by missing value. In Sect. 5.3 we will present the results of the estimation. Next session introduces our independent variables.

5.2 The variables

We identify three types of independent variables.

5.2.1 Physical network effects

Physical network effects are associated to the availability of complementary equipment in the market, as well as to the degree of compatibility between the currently deployed standard and the alternative to be chosen. As argued above, many firms that adopted Fast Ethernet had previously adopted Ethernet. To understand whether this previous status may have influenced the timing of Fast Ethernet adoption, we

[7] We thank an anonymous referee for pointing out that this estimation strategy was more appropriate given the features of our data.

[8] See Stewart (1983) for a description of the method and Tedds (2006) for an application.

asked respondents to measure on a four points scale the importance of backward compatibility when planning a migration to a new standard and/or technology. Responses were used to construct the variable Techcomp that varies between 1 ("not at all important") and 4 ("very important"). We expect firms that score high on this variable to adopt early Fast Ethernet. Since this standard is compatible with Ethernet, its advantages (with respect to alternative high speed standards) are higher, the more firms are interested in maintaining backward compatibility.

5.2.2 *'Virtual' network effects*

As argued in Sect. 2, virtual network effects are mainly generated by information spillovers about the technology and the payoff from its adoption. Spillovers may arise from the size of the existing network of Fast Ethernet adopters, the rationale being that, by observing past behaviours, firms draw information about the characteristics of Fast Ethernet and the opportunity to upgrade. To capture the effect of spillovers from past adoption, we asked a firm to report how desirable is to be compatible with most of the other firms when buying a new product supporting a specific standard. Four possible options were given ranging from "not at all desirable" to "extremely desirable". Given that responses to this question clustered in the upper two categories ("desirable" and "extremely desirable") we construct the variable Bandwg3 equal to one if this type of spillover is desirable. This type of spillover may speed up or delay adoption.

In Sect. 3 we also argued that adoption can be influenced by the extent of previous learning accumulated in the use of software to manage the network, particularly when this software is 'vendor specific'. To capture this influence on the speed of upgrade, we asked firms to report how important it is to buy from a vendor with whom the firm has entertained commercial relationships in the past. Again responses were coded on a four point scale, with "not at all important" and "extremely important" as anchor points and were used to construct the variable Vendcomp that varies between 1 and 4. We split this variable in two. Vendcomp3 (= important) and Vendcomp4 (= extremely important) are dummy variables equal to one if vendor compatibility is important or extremely important respectively and zero otherwise. This variable captures the preference for vendor compatibility. This preference can either speed up or delay adoption in those cases in which buyers do not want to run the risk of being locked-in to a specific vendor. We do not make hypotheses on the direction of the impact of this effect on timing of adoption.

5.2.3 *Expectations*

We distinguish between two types of expectations: price expectations and technological expectations. To capture the influence of price expectations on the decision to adopt, we asked firms to assess on a four points scale (with "not at all influential" and "highly influential" as anchor points) the extent to what 'waiting for the price of the technology to decline' was influential on their decision to migrate to the new technology. We then used the responses to construct the variable Priceexp that varies between 1 and 4.

By the same token, the role of technological expectations was assessed by asking firms to rate on the same type of scale to what extent 'waiting for the technology to mature' was influential and by constructing the variable Techexp that varies between 1 and 4. On the basis of the existing theoretical and empirical literature we expect, in both cases, that firms with a higher score are more likely to delay adoption of Fast Ethernet.

5.2.4 *Additional variables*

In the selection equation, we control for two additional determinants of adoption: firm size and switching costs. Firm size is expected to play an important role in adoption for at least two reasons. First, as stressed in Sect. 2, larger firms have generally more resources to invest, may enjoy higher returns from adoption and are usually more prone to risk. Second, the larger the firm, the wider the network currently in use and the more likely it is that congestion will be experienced. Demand for high speed standard such as Fast Ethernet is higher in highly congested networks. We should therefore expect larger firms to have a higher probability of adoption. Our measure of size is the firm annual revenues in the latest year preceding the survey. To be more precise, we asked respondents to identify the firm's annual revenues (Rev) along six possible asymmetric intervals varying between 1 ("Rev $\leq$ 50K euros") and 6 ("Rev $>$ 10M euros"). Firms in our sample are unevenly distributed across the six intervals with no firms in the smaller size categories and the majority concentrated in the upper two categories (1M euros < Rev < 10M) and (Rev > 10M). To construct our variable Size we took the natural log of the mean value of each interval plus the right border of the lowest interval and the left border of the top interval.

As argued in Sect. 3, switching costs may also affect Fast Ethernet adoption. We have identified three cost components of running a LAN: Capital Equipment costs deriving from the purchase of the hardware necessary to implement the standards (i.e. hubs, switches, routers); Facilities costs (i.e. costs for wiring/cabling, equipment and software maintenance); Personnel/Human capital costs (i.e. costs for network design and management support and training). We asked firms to give an estimate of the share of each component over the total. Swcost is a variable that considers the sum of the share of capital and personnel costs. We expect firms with higher switching costs to have a lower likelihood to adopt.

5.3 Results

A total of 98 firms answered the questionnaire (24 *Pioneers*, 37 *Early adopters*, 14 *Laggards* and 23 *Non adopters*). In this section we present the results from our estimation, accounting for selection bias. We will first present the results of the interval regression which is the best suited for our data. Then, just for comparison purposes, we will show the estimations from the ordered probit model. Finally, we will carry out an explorative sensitivity analysis and estimate a multinomial logit in the second stage. As mentioned above, before proceeding with the estimation we must account for sample selection bias. Table 5 reports the results. Model (1) is the selection equation estimated on the full sample of 98 firms.

Results indicate that price expectations have a strong and negative impact on the probability to adopt, a result which is consistent with the literature reviewed in Sect. 2 predicting that expectations of future price decline are generally associated to adoption delays and/or non adoption. Size is positive and highly significant. [9] The coefficient of Swcost, our proxy for the total cost of running the network, is negative, thus suggesting that high switching costs decrease the likelihood of adoption. Although consistent with the theory predicting that switching costs are an important source of inertia in adoption, the coefficient is not significant. Marginal effects, reported in column (2), allow us to better assess the impact of the variables. This is particularly important for size. Indeed, our results suggest that a one percent increase in firm's revenues brings about an almost ten percent increase in the probability of adoption.

Model (3) reports the estimates of the interval regression accounting for selection bias. We employ as covariates the same explanatory variables used in the estimation of the selection equation with the exclusion of Swcost.[10] To these variables we add Techcomp, our proxy for physical NE, the proxies for virtual NE (Vendcomp, and Bndwg) and a measure of technological expectations (Techexp). We control for sample selection bias by including the selection variable $\hat{\lambda}$.[11]

Results from the interval regression controlling for selection bias show that price expectations and virtual network effects significantly impact on timing of adoption.[12] In particular, the positive coefficient for Priceexp suggests that firms that take into account

[9] This result holds when using alternative proxies for size such as the number of employees, the number of connected network nodes, and the number of connected company sites. Bigger firms have larger networks in place and are more likely to experience congestion problems. Upgrading to Fast Ethernet is a way of reducing congestion.

[10] Swcost is excluded to ensure some variability between the two steps of the model, in order to reduce simultaneity problems leading to possible spurious significance of sample selection effects (Battisti and Stoneman 2005) and because switching costs are traditionally considered to influence the probability to adopt rather than the timing of adoption. The same applies for Size, though it is included in the regression. Including this variable provides us with a simple test of its validity as instrument by checking whether it is significant in the selection equation but not in the equation of the second stage. Thanks to an anonymous referee for this suggestion.

[11] The estimates reported are computed by the two stages approach in which the mills ratio from the probit regression is used in the second stage. Standard errors are corrected via bootstrapping. In particular we resample (with replacement) from the entire sample and repeat the procedure 200 times.

[12] At the bottom of Table 5 we report the McKelvey & Zavoina R^2 as a measure of goodness of fit and a sigma statistics. The R^2 is constructed as: $Var(\hat{y} - y^*)/Var(y^*)$ using the variance of the latent variable y^* and the variance of the latent predicted variable $\hat{y}$. The sigma statistics is the equivalent of the standard error of estimate in a OLS regression.

Table 5 Determinants of timing of adoption. Interval regression model. Estimates with sample selection dependent variables: Lower and Upper

Independent variable	Selection equation (Probit)	Marginal effects	Regression model‡(Interval regression)
	(1)	(2)	(3)
Size (Log)	0.354 [0.125]***	0.099 [0.034]***	−2.026 [2.125]
Priceexp	−0.572 [0.196]***	−0.159 [0.050]***	4.710 [2.794]*
Swcost	−1.236 [1.095]	−0.345 [0.0305]	
Techexp			−1.110 [2.169]
Vendcomp3 = Important (Virtual NE)			−5.818 [2.556]**
Vendcomp4 = E. Important (Virtual NE)			−5.141 [13.620]
Bandwg3 = Desirable (Virtual NE)			1.913 [2.511]
Techcomp (Physical NE)			−0.041 [1.461]
$\hat{\lambda}$			−25.008 [14.801]*
Constant	−1.930 [1.883]		37.033 [32.450]
Observations	98		Observations: 75
Log Pseudo LL	−45.47		McKelvey & Zavoina's Rsq: 0.088
Wald Chisq	12.97***		Sigma: 7.990
Pseudo Rsq	0.148		

* Denotes 10% significance level, ** denotes 5% significance level, *** denotes 1% significance level

‡ Bootstrapped standard errors in brackets

future price declines in their decision to adopt Fast Ethernet tend to delay adoption.[13] This result is consistent with the existing theoretical and empirical literature (reviewed in Sect. 2) on the impact of expectations on the speed of adoption. The negative coefficient for VENDCOMP3 our measure of firms' preference for vendor compatibility, indicates that, ceteris paribus, those firms that consider important to maintain compatibility with their vendor adopt Fast Ethernet more quickly (nearly six months) than the other firms. This result suggests that preference for a specific vendor tends to speed up the upgrade. Recall that, as argued above, preference for vendor compatibility may, in principle, also delay the upgrade to the extent to what repeated purchases from the same vendor may also increase the fear of becoming locked in to a specific manufacturer. Our findings do not seem to support this hypothesis. This is probably due to the fact that, at the time of the survey, Fast Ethernet was a mature standard with known characteristics. Non proprietary management software for Fast Ethernet was widely available. Thus chances of being locked in to a specific vendor were small. The selection variable $\hat{\lambda}$ is statistically significant. This is an indication that correcting for sample selection bias is important both from a conceptual and from a statistical viewpoint. Unless we control for adoption,

[13] It can be argued that this variable just captures the impact of budget constraints on adoption choices. This is not plausible in our case. If some respondents wait for the price to decline because they cannot afford the product at a high price, we should expect them to be particularly sensitive to the economic variables influencing adoption. If the variable PRICEEXP captures this sensitiveness instead of the impact of expectations, it should be positively and significantly correlated to other 'budget related' variables. Among these variables, cost of adoption is the most relevant. In the questionnaire, respondents' evaluation of adoption costs is captured by two different questions. One question asks to rank on a four point scale how important high costs of adoption are as a barrier for the decision to upgrade their existing technology. Answers to this question are coded into the variable (COST_BAR). Another question asks how important minimising the capital cost of upgrading is as an objective when deciding to invest in networking. In this case, the corresponding variable is (UP_COST_OB). It can be noted that PRICEEXP is negatively and significantly (albeit weakly) correlated with COST_BAR (−0.1632), and positively although not significantly correlated with UP_COST_OB (0.0034). This seems to contradict the hypothesis that PRICEEXP captures the impact of budget constraints on adoption choice.

the estimated coefficients of the explanatory variables of the timing equation turn out to be biased. This indicates that the decision to upgrade from Ethernet to Fast Ethernet and timing of adoption are not disjointed. Finally, it is interesting to note that the coefficient for our proxy for size is negative and non significant, thus suggesting that it is a valid instruments in the selection equation (see also footnote 10). Altogether, our results stress that both expectations and network effects are important determinants of the speed of upgrading. However, the evidence we found is quite mixed. Anticipating technological improvements does not seem to significantly influence timing of adoption as the coefficient of TECHEXP shows. Again, this follows from Fast Ethernet being a mature technology, which is less likely to experience further improvements in the near future. Moreover, BANDWG3, our second proxy for virtual network effects, and TECHCOMP, our proxy for physical network effects, are never significant.

We explore the robustness of our results by running two additional models: an ordered probit model and a Multinomial Logistic. As mentioned above, the ordered probit model is not the most appropriate when the thresholds defining the categories of the dependent variable (*Status*$_j$ in our case) are known. Moreover, for the ordered probit to be effective, it would be necessary that the data meet the proportional odd assumption, which they do not in our case. Thus, we provide these results for comparison purposes only and do not delve at length into them.[14] Table 6 reports the results. Overall, these results tend to mirror those from the interval regression in terms of coefficients' sign and significance. However, the predicted values obtained from the regression should be interpreted in terms of probability of belonging to the categories rather than in terms of marginal effects.

Finally, we can compare our interval regression results with the estimates from a Multinomial Logistic model. Again, given that our dependent variable *Status*$_j$ is inherently ordered, a Multinomial Logistic regression is less indicated than the interval regression. However, it provides separate coefficients for each covariate. Since we are interested in explaining heterogeneity in firm behaviour, we are able to single out the determinants of differences of behaviour across categories of adopters and further inspect our results. Finally, in his seminal paper on the role of expectations Weiss (1994) used a similar estimation approach. Results are summarised in Table 7.[15] In this case, positive coefficients indicate that higher values of the covariate make it more likely that the firm will be in the current category of the variable *Status*$_j$. Negative coefficients indicate that higher values of the covariate decrease the likelihood of being in the current category of the variable *Status*$_j$. The selection variable $\hat{\lambda}$ now comes from a logit model in the first stage.

Table 6 Determinants of timing of adoption. Ordered probit model dependent variable: status

Independent variable	Ordered probit
	(4)
Size (Log)	−0.254 [0.262]
Priceexp	0.589 [0.352]*
Techexp	−0.139 [0.213]
Vendcomp3 = Important (Virtual NE)	−0.728 [0.311]**
Vendcomp4 = E. Important (Virtual NE)	−0.643 [0.757]
Bandwg3 = Desirable (Virtual NE)	0.239 [0.278]
Techcomp (Physical NE)	−0.005 [0.169]
$\hat{\lambda}$	−3.13 [1.785]*
μ_1	−4.635 [3.924]
μ_2	−3.133 [3.897]
Observations	75
Log Pseudo LL	−71.20
Wald Chisq	11.45*
Pseudo Rsq	0.075

* denotes 10% significance level, ** denotes 5% significance level, *** denotes 1% significance level

Robust standard errors in brackets

[14] In carrying out this estimation we follow Demoussis and Giannakopulos (2006).

[15] This implementation deviates from the two-step standard Heckman procedure in the sense that the effects of sample selection do not follow the traditional (simple linear) approach. We have not adjusted the standard errors for the estimated Multinominal Logistic coefficients. Making this type of adjustment requires quite a complex procedure (see van de Ven and van Praag (1981) for a description and Gooroochurn and Hansley (2006) for an application) that goes beyond the scope of our sensitivity analysis, which aims instead at providing a preliminary exploration of the effect of selection on timing of adoption.

The second column of Table 7 reports the results from the comparison between *Pioneers* and the *Laggards*. Results are similar to previous results from the interval regression. Spillovers linked to vendor compatibility speed up adoption by increasing the probability of being *Pioneers*. Price expectations instead delay adoption as suggested by the negative and significant coefficient. The selection variable is still significant. When we compare *Early adopters* and *Laggards* (see column three), price expectations and vendor compatibility still matter, but the coefficient of TECHCOMP is also positive and significant albeit weakly. This suggests that physical network effects matter in this case. Recall that this variable measures the importance of maintaining backward compatibility when migrating to the new standard. These results suggest that firms with a high preference for backward compatibility have a higher probability of being *Early adopters* than *Laggards*. Overall, it can be argued that preference for (vertical) backward compatibility generally tends to speed up adoption. This result is somewhat expected given the compatibility between Ethernet and Fast Ethernet. Finally, it can be noted that, contrarily to what highlighted in the case of interval regression, our proxies for size are now positive and significant, suggesting that bigger firms tend to adopt relatively earlier with respect to smaller ones.

All in all, the results from our exploratory sensitivity analysis seem to confirm the estimates of the interval regression concerning the direction of the impact of price expectations and virtual network effects related to vendor compatibility on timing of adoption. However, by providing separate coefficients for each category of adopters, we have been able to gain additional insights on the role of firms' heterogeneity. In particular, physical network effects seem to become significant only for certain categories of firms (*Early adopters*) and not for others.

6 Conclusions

This paper took a firm level approach to study the factors affecting the timing of adoption of Fast Ethernet, a high speed LAN standard. Relying on a detailed survey of 128 SMEs active in the computer service industry in Italy, we were able to collect information on both the technologies in use and the determinants of adoption decisions by LAN managers. The information was used to study the impact of expectations and network effects on timing of adoption of different types of firms categorised by speed of adoption. Controlling for sample selection bias, the following results were found.

Table 7 Determinants of timing of adoption. Exploring the robustness of results. Multinomial logit model estimation. dependent variable: STATUS

Independent variable	Multinomial logit		
	[0 vs. 2]	[1 vs. 2]	[1 vs. 0]
Size (Log)	0.585 [0.554]	0.936 [0.523]*	0.351 [0.392]
Priceexp	−1.613 [0.930]*	−1.814 [0.898]**	−0.200 [0.541]
Techexp	0.276 [0.599]	−0.150 [0.587]	−0.426 [0.447]
Vendcomp3 = Important (Virtual NE)	2.382 [0.928]**	2.135 [0.875]**	−0.247 [0.684]
Vendcomp4 = E. Important (Virtual NE)	1.527 [1.665]	0.531 [1.764]	−0.996 [1.414]
Bandwg3 = Desirable (Virtual NE)	−0.951 [0.942]	−0.352 [0.851]	0.599 [0.716]
Techcomp (Physical NE)	0.488 [0.750]	1.204 [0.713]*	0.717 [0.465]
$\hat{\lambda}$	6.707 [3.896]*	5.886 [3.827]	−0.820 [2.127]
Observations		75	
Log Pseudo LL		−63.35	
Wald Chisq		27.27**	
Pseudo Rsq		0.177	

* Denotes 10% significance level, ** denotes 5% significance level, *** denotes 1% significance level

Robust standard errors in brackets. Constant term omitted. J = 0 Pioneer, J = 1 Early Adopter, J = 2 Laggard

First, we provided evidence to support the hypothesis that expectations generally tend to delay adoption. This confirms the conclusions of the existing theoretical literature on the subject, as well as of the previous empirical study carried out by Weiss (1994), although in our case it is price rather than technological expectations that seem to play the most important role. Second, we presented two pieces of evidence on the impact of network effects on timing of adoption. First, we found that indirect network effects impact significantly on timing of Fast Ethernet adoption. Second, the level of detail of our survey enabled us to distinguish different types of indirect network effect. We found that virtual network effects generally speed up adoption. In particular, our findings suggest that the presence of informational spillovers from vendors speeds up adoption of any category of firms. Preference for backward (vertical) compatibility also speeds up adoption though it positively impacts only on *Early adopters*. This result supports the view that in technical systems physical indirect network effects matter for adoption. Finally, in the sample selection equation, we also found that large firms are more likely to adopt.

Although promising and encouraging, especially given the scanty existing empirical evidence on the role of expectations, these preliminary findings are subject to some limitations. First, we have 98 firms in our sample, not a large number. Even if this number is comparable to previous studies in the field that adopted a similar methodology (Weiss 1994), it constrains the number of independent variables that can be used in the estimations. An attempt to extend the sample by surveying more firms is currently being carried out. Working on a larger sample of firms would allow us to control for firm specific effects, other than size, that may influence the speed of upgrading such as firm competencies. Second, the survey targeted firms from the computer service industry (NACE 72) only. These are generally high tech firms with a high propensity to adopt new technologies. As a consequence, our results may have over-sampled the number of Fast Ethernet adopters. Moreover, if patterns of adoption are sectoral specific, as previous studies highlighted (Windrum and de Berranger 2003), we should expect firms from low tech sectors to behave differently. Extending the survey to low-medium tech industries would help to explore further this issue. Finally, this paper considered the case of two mature standards. Ethernet has been the dominant standard for LANs since the end of the 1980s, Fast Ethernet has been commercialised since mid 1990s. It may be argued that focussing on the decision to adopt a mature standard may lead to an underestimation of the role of technological expectations as determinants of the speed of upgrading as indeed we found. While this choice does not affect the relevance of the results with respect to the differences we found across the different categories of adopters, focusing on less mature standards may bring different results, particularly concerning the role of technological vis-à-vis price expectations as determinants of the speed of upgrade. We will explore all these issues further in future work.

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