Target Age and the Acquisition of Innovation in High-Technology Industries

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External acquisition of new technology is a growing trend in the innovation and product development process, particularly in high-technology industries, as firms complement internal research and development efforts with aggressive acquisition programs. Yet, despite its importance, there has been little empirical research on the timing of acquisition decisions in high-technology environments. Should organizations wait until more information is available about the target and its markets so that a better valuation can be obtained? Or should the target be acquired early to lower acquisition cost and gain early access to key technologies? Applying an event study methodology to technology acquisitions in the telecommunications industry from 1995 to 2001, we find evidence that supports acquiring early in the face of uncertainty. Our analytical model and empirical analysis uncover two characteristics of young targets that drive benefits from early acquisitions—flexible growth options that provide greater opportunities for synergistic fit, and greater valuation uncertainty that leads to lower prices. However, the negative effect of target age on acquirer value is partially mitigated if the target has recent patents or is privately held. In addition, the probability of acquisition is higher for targets that have signals of higher quality, and lower for targets that have superior access to capital and resources.

1. Introduction

The importance of innovation and new product development is highlighted through a vast literature on the topic in operations management (Kalaignanam et al. 2007, Krishnan and Ulrich 2001, Terwiesch et al. 1998), marketing (Hauser et al. 2006), strategy (McGrath and Nerkar 2004), and organizational behavior (Brown and Eisenhardt 1995). Typical issues examined in this literature include concept development (Ulrich and Ellison 1999), supply chain design (Lee and Tang 1997), development process management (Bhuiyan et al. 2004, Ding and Eliashberg 2002, Terwiesch and Loch 1999), the role of patents (Clark and Konrad 2008, Ziedonis 2004), and the impact of product development failure on firm value (Girotra et al. 2007). Comprehensive surveys appear in Shane and Ulrich (2004) and Krishnan and Ulrich (2001). Barring a few exceptions (e.g., Ahuja and Katila 2001, Higgins and Rodriguez 2006), the primary focus has been on the product development and innovation process internal to the firm.

In high-technology industries, external acquisition of new technology plays a vital role in the product development process (Higgins and Rodriguez 2006). Because time-to-market pressures often render internal development too slow, firms like Microsoft and Cisco augment internal research and development (R&D) with aggressive acquisition programs that are becoming increasingly important as a way for "maturing strategic buyers to access new growth opportunities" and to place "bets on new ideas or technologies" (*Financial Times* 2006, p. 20). Acquisitions also add a key exploratory component to product development (Chesbrough 2003) and allow acquirers to fill gaps in product portfolios (Ding and Eliashberg 2002). They foster a strong market for ideas, providing incentives for entrepreneurs to sweat, to risk, and, maybe, to exit wealthy (Gans and Stern 2003). Thus, entrepreneurial firms often specialize in innovation and R&D, and rely on the specialized assets of the larger acquirer for complementary downstream activities in the new product development process (Chan et al. 2007). However, despite its importance, technology acquisitions have received limited attention in the product development literature, and profit through acquisitions is not well understood in high-technology environments where acquisitions foster innovation rather than conglomerate diversification.

We focus on the effect of a fundamental characteristic of a target, specifically target age, on buyer profit in high-technology environments. Target age is an objective and observable differentiator (even for small, private startups) that has received considerable media and industry attention, but limited research consideration. From the perspective of the buyer, the emergence of an early stage company begins an inherent conflict between risk and safety. Should organizations wait until more information is available about the target, its technology, its product, and the market so that a better valuation can be obtained? Or should the target be acquired early to gain quick access to key technologies, reduce integration problems, and lower the cost of the acquisition? Even conventional proverbs offer conflicting advice as managers may choose to "look before they leap" or alternatively they may believe that "he who hesitates is lost." This ambiguity is also reflected in the trade literature, where target age is a frequent focal point of the discussion, with conflicting opinions on its role (*Financial Times* 2006, Schiesel 2000).

The product development literature highlights a similar dilemma between the use of proven technologies and unproven (but promising) technologies in developing new products (Bhattacharya et al. 1998, Chaudhuri and Tabrizi 1999, Iansiti 1995). Analytical models demonstrate that selecting only proven technologies for inclusion in product design (Krishnan and Bhattacharya 2002, Loch and Terwiesch 2005), or forcing early finalization of specifications (Bhattacharya et al. 1998, Jain and Ramdas 2005), may not be optimal in dynamic environments. The fundamental insight from the analytical models is that flexibility is valuable in dynamic environments because it affords managers the ability to change course as better market information becomes available (Huchzermeier and Loch 2001).

We examine acquisitions made by equipment manufacturers within the telecommunications industry during 1995–2001 because of the industry's emerging standards, deregulation, numerous innovations, acquisition volume, and uncertainty during that period (Warner et al. 2006). Evaluation of acquisition opportunities is particularly difficult in these environments because it is uncertain which technologies will dominate or how the markets will evolve. We develop our hypotheses through an auction framework (Milgrom 1989) that identifies the salient characteristics of a target in dynamic environments, combines these characteristics into a precise model of the buyer's profit from the acquisition, and explores how target age affects the variables in the model. We also identify factors that moderate this relationship, and we define situations where target age is likely to have a greater impact. We then test

these hypotheses through empirical analysis using proportional hazard and abnormal return models. Through this analysis, we identify a few key reasons behind an age effect.

There are three primary contributions of this research. First, theoretical underpinnings of previous empirical research have focused on the financial drivers of acquisitions, such as economies of scale (Lambrecht 2004), managerial misincentives (Moeller 2004), equity misvaluations (Shleifer and Vishny 2003), and free cash flow (Jensen 1986). Although these variables have considerable explanatory power in traditional environments, the analytical model in this paper provides a new set of value drivers for the dynamic and high-technology environment we study. Specifically, the analytical model focuses on the trade-off between the technological flexibility afforded by an early stage target and the uncertainty associated with its valuation. Second, we empirically investigate the impact of an observable and objective characteristic of the target (specifically target age) that has been the source of considerable debate in the trade literature but has received scant attention in the academic literature. Recent research has focused on some related aspects of acquisition timing, although not specifically on the effect of target age on buyer profit. In general, buyers profit more from acquisitions made toward the beginning of an industry acquisition wave (Carow et al. 2004). Regarding target age, older targets decrease the rate of acquirer new product introductions (Puranam et al. 2006), but lead to more immediate revenues (Chaudhuri et al. 2005). Finally, whereas the new product development literature highlights the role of patents in protecting innovation in high-technology industries (Clark and Konrad 2008, Ziedonis 2004), we also provide empirical evidence that recent patents indicate the presence of growth options in a target, make an older target more akin to a younger company, and retain value for the acquirer as the target ages.

The rest of this paper is organized as follows. In the next section, we develop our hypotheses on the impact of target age on buyer profit. Then, we detail the data and methodology used to test the hypotheses. Next, we discuss the results of the analysis. Finally, we summarize the findings of the research and outline future research directions.

2. Theory and Hypotheses Development

2.1. An Auction Framework for Technology Acquisitions

An auction perspective provides an insightful theoretical basis for precisely modeling the profit for the buyer in technology acquisitions for four reasons.

First, the high-velocity environment of the communications industry has fostered a large number of startup organizations that focus on technology development and view acquisitions as an attractive exit strategy. Similar to an auction environment, the objective of the startup firm is to discover an appropriate selling price and maximize its revenue through the sale. Second, there are many buyers within the industry who view acquisitions as an effective strategy to complement their internal R&D efforts. The existence of several potential buyers simulates an environment that is similar to an auction. Each potential buyer has an implicit valuation of the target based on their own unique capabilities, although they may not submit explicit bids. Subsequently, the target is sold at the highest price possible, if the offered price is above the reserve price of the seller. Third, the auction framework can take into account several variables that are important in dynamic environments, such as the uncertainty associated with buyer valuations, the reserve price of the seller based on its stage of development, and the ability of a buyer to have private valuations of the technology based on synergistic fit (Milgrom 1989). Finally, the well-developed literature on auctions provides a set of readily available and precise tools to analyze the technology acquisition environment.

In the auction model that follows, we view a target in a technology acquisition as a combination of *mature operations* and *unexplored growth options*. Mature operations have tangible products or services, established customers and revenue streams, and well-defined business models. We also include in mature operations those growth opportunities that are within the normal business operations of the target and that can be effectively exploited by the target in due course. For example, incremental revenue opportunities with existing or closely related products that the target may not have fully exploited yet (but has the capability to do so in the future) are included in the mature operations of the target. Unexplored growth options include technologies of the target firm that have the potential to generate profits in the future but do not currently have well-established products, customers, and revenue streams, and that cannot be fully exploited by the target on its own with its existing capabilities. For example, unexplored growth options include new technologies developed by the target that require downstream capabilities (such as access to capital, sales channels, or complementary products) that the target does not possess and cannot easily acquire. Thus, unexplored growth options capture the concept of synergistic fit, where acquirers can develop the technology in ways that exploit their own unique strengths.

For mature and established operations, there is little opportunity for synergistic private value from the acquisition. Therefore, whereas individual signals of this value may vary, the value of the mature operations is largely common to all buyers. In the auction environment, this can be captured through a *common value* auction framework that has been used to analyze mineral rights auctions in the literature (Milgrom 1989). Growth options, on the other hand, provide the greatest opportunity for synergistic fit with the buyer, because each buyer can develop the technology and its market differently by taking advantage of its own unique resources and business models. Thus, each buyer has a *private value* for the unexplored growth options associated with the target. Consequently, similar to many other contexts that arise in practice (Goeree and Offerman 2002), technology acquisitions have elements of both common value and private value auctions, with mature operations and unexplored growth options representing common value and private value components, respectively.

2.2. Uncertainty, Flexibility, and Target Age

Consider an auction with n potential buyers for the target at age t. Let $v_i(t)$ be the value signal of buyer i for the mature operations of the target at age t. For simplicity, we assume that the common value signals (v_i) are generated from a uniform distribution with mean $\overline{V}(t)$ and range $R_v(t)$. The mean, $\overline{V}(t)$, captures the expected value of the mature operations of the target at age t. There are two reasons why the expected value of the target's mature operations is likely to increase with age. As the target ages, the firm exploits some of its growth options and they become part of its mature operations. Also, the size and scale of its existing operations may increase over time through organic business growth. Thus, although it is not required for our derivations, we expect $\overline{V}(t)$ to be an increasing function of target age t.

The range, $R_v(t)$, captures the *valuation uncertainty* associated with the mature operations of the target at age t. When $R_v(t)$ is large, the buyer valuations of the mature operations of the target are more dispersed, and there is greater uncertainty associated with the valuation. Conversely, when all valuation uncertainty is removed, the buyer valuations of the mature operations converge to the true value, and $R_v(t)$ approaches zero. Prior research identifies two types of uncertainty in high-technology industries—market uncertainty and technology uncertainty (Warner et al. 2006). In addition, buyers also face a third type of uncertainty specific to the management and operations of the target firm. As the target ages, it has a longer track record of operations, and more information is available to the buyer about the target, its operations, and management. Furthermore, its technology

matures with age and there is a better understanding among potential buyers of its feasibility and benefits. Likewise, as the target matures, buyers have better knowledge of its markets and the revenue potential of its technology. Thus, all three types of uncertainty decrease with target age and the buyer has a more precise valuation. Consequently, $R_v(t)$ is a decreasing function of target age t.

Similarly, let $p_i(t)$ be the private valuation of the unexplored growth options of the target at age t for bidder i. We assume that the private values, $p_i(t)$, are uniformly distributed between 0 and $R_p(t)$. Thus, potential bidders vary in their ability to exploit the unexplored growth options of the target. The range, $R_p(t)$, is a measure of the *flexibility* of the growth options of the target to develop along different directions based on the unique capabilities of the acquirer. Although mature operations are already established and benefit less from the expertise or resources of a larger acquirer, growth options provide greater opportunity for the acquirer to add value. For example, the acquirer can provide commercialization expertise or make subsequent amplifying investments that increase the value of the technology, such as lobbying to enact favorable legislation, participating in industry organizations to promote compatible standards, and exploiting existing customer relationships to generate demand (McGrath 1997). Acquirers can also exploit their existing complementary assets (such as marketing expertise and R&D capability) to increase the value of the target's growth options. Acquirers vary in such capabilities, and the range $R_p(t)$ captures this diversity.

There are three reasons why this flexibility decreases with target age. First, as the target ages, its technology becomes more mature and defined, and there is less flexibility for opportunistic evolution. Second, as the target ages, the market for its technology becomes more defined and competition becomes more entrenched, thereby reducing flexibility for the buyer. Third, as the target ages, it develops entrenched processes and practices and its structural inertia increases (Hannan and Freeman 1984). This reduces flexibility to develop the target along unique paths and reduces the opportunity for private valuations. Consequently, $R_p(t)$ is a decreasing function of target age t.

Because the private valuations of the unexplored growth options of the target ($p_i(t)$) are drawn from a uniform distribution between 0 and $R_p(t)$, and $R_p(t)$ is a decreasing function of target age, the mean of the private valuations ($R_p(t)/2$) also decreases with target age. There are two reasons behind this assumption. First, existing growth options lose value over time, especially in high-technology industries where the window of opportunity to exploit a new technology is relatively short. Second, the firm is able to

convert some of its growth options into mature operations over time. Thus unexplored growth options transition over time into mature operations and the expected value of mature options $\bar{V}(t)$ may be an increasing function of target age.

In summary, $R_v(t)$ and $R_p(t)$ capture two fundamental dimensions in the acquisition of target firms in dynamic environments. As the target ages, the uncertainty associated with its valuation decreases as more information is available and the target has a longer history of operations. On the other hand, its structural inertia increases with age and its technology becomes more mature, thereby reducing the flexibility available to the acquirer to develop the target in unique ways that exploit its private capabilities.

2.3. Modeling Assumptions and Implications

Following (Goeree and Offerman 2002), we assume that the best estimate of actual value ($V(t)$) for the common value portion of the target (mature operations) at age t is given by the average of the n potential buyer value signals ($E(V(t)) = \bar{V}(t) = \sum_{\forall i} v_i(t)/n$), where i indicates a potential buyer and $\bar{V}(t)$ is the mean of the uniform distribution from which the value signals are drawn. That is, we assume that the buyer value signals at any target age are dispersed around the true value, but they are unbiased.

We model the technology acquisition environment as a first-price, sealed bid auction for three reasons. First, there are several potential buyers in this industry who augment internal R&D efforts through acquisitions. In our sample, there were 96 unique buyers within the equipment manufacturer segment of the telecommunications industry. Although they have private valuations of the target based on their own capabilities, they do not submit formal bids unless they determine that their bid has a reasonable chance of acceptance. Thus, in contrast to English auctions where all valuations are successively revealed, buyers in our environment have reduced ability to see the private valuations of most other bidders when they submit their bids. Second, whereas the negotiations process can be complex with offers and counteroffers, the first price, sealed bid auction provides a tractable approximation that captures the fundamental notion that price paid by the buyer is based on the next best option available to the target (such as the next highest bid value). Third, Goeree and Offerman (2003, p. 606, Proposition 4) show that if the best estimate of actual value for the common value portion of the target is given by the average of the n potential buyer value signals, and each bidder knows the magnitude of the range of bidder valuations, then (a) profit to the buyer and (b) revenue to the seller remain the same for all the standard auction formats. Because our hypotheses are based on buyer profit and seller

revenue, the choice of the auction format does not affect the derivation of our hypotheses.

We also assume that the bidder value signals ($v_i(t)$ and $p_i(t)$) are drawn from uniform distributions, and that each bidder knows the magnitude of the range ($R_v(t)$ and $R_p(t)$) of these distributions. Whereas uniform distributions make the mathematical derivations of optimal bids tractable, the intuition behind the hypotheses hold true for other common distributions, and we carefully explain this intuition while stating the hypotheses. The uniform distribution assumption allows us to illustrate this intuition effectively. Because buyers are usually firms within the same industry, it is reasonable to expect that they have some estimate of the valuation uncertainty ($R_v(t)$) associated with the target. Likewise, potential buyers have knowledge of the capabilities of other potential buyers in the industry and have reasonable estimates of the magnitude of the range of private valuations ($R_p(t)$) of the target's technology. Our hypotheses do not require precise but only approximate knowledge of the magnitude of $R_v(t)$ and $R_p(t)$.

2.4. Optimal Bids and Winner Profits
In this section, we derive the expressions for optimal bids and winner profits based on Goeree and Offerman (2002). Consider a target of age t. At the time of making a bid, a bidder has two signals of value, $v_i(t)$ and $p_i(t)$, for the mature operations (v_i) and growth options (p_i) of the target, which are drawn from uniform distributions with range $R_v(t)$ and $R_p(t)$, respectively. The signal of target value for bidder i is therefore ($p_i(t) + v_i(t)$), but this is not the optimal bid because of the familiar "winner's curse" in common value auctions. In general, combining the two value signals ($v_i(t)$ and $p_i(t)$) into a single signal that can be used to formulate optimal bids is a difficult problem (Milgrom 1989). However, Goeree and Offerman (2002) show that in auctions with common value (v_i) and private (p_i) signals, where the best estimate of the common value portion is the average of the bidder common value signals, the Nash equilibrium, optimal bid for any bidder i in a first price auction is an increasing function of the combined signal $s_i(t) = p_i(t) + v_i(t)/n$. In the appendix, we derive the expression for optimal bids (b_i) as a function of $s_i(t)$. Here, we provide the basic intuition behind the expression. In Equation (1), which follows directly from Goeree and Offerman (2002, Proposition 1), $R_s(t)$ is the range of the uniform distribution from which the $s_i(t)$ values are drawn, and $R_s(t) = R_p(t) + R_v(t)/n$. The optimal bid is

$$b[s_i(t)] = p_i(t) + E[V(t) \mid s_i > s_j \ \forall j \neq i] - \frac{R_s(t)}{n+1}. \quad (1)$$

The first term on the right-hand side is the private value of the target's unexplored growth options for

bidder i. The second term represents the expected value of the target's mature operations, if the combined signal $s_i(t)$ of bidder i is the highest among all bidders (that is, the expected value of mature operations is calculated by bidder i assuming that she wins the auction). The third term, which represents the amount by which each bidder reduces her bid to earn a profit (bid discount), is equal to the expected difference between the highest and second-highest combined signals ($s_i(t)$) of n bidders. Thus, it follows that the profit to the buyer (winner in the auction) over and above the price paid for the target is given by

$$\pi_w(t) = \frac{R_s(t)}{n+1} = \frac{R_p(t) + R_v(t)/n}{n+1}. \quad (2)$$

Equation (2) forms the basis for the hypotheses presented in this paper, and an intuitive understanding is important. The buyer's profit from the acquisition is affected by three factors: (a) the opportunity for synergistic fit captured by the range of private valuations of the unexplored growth options of the target ($R_p(t)$), (b) the valuation uncertainty associated with the mature operations of the target captured through the range ($R_v(t)$) of the common value signals, and (c) the number of potential bidders (n) for the target. As in the familiar private value auction framework (Milgrom 1989), a larger range of private values ($R_p(t)$) increases the distance between the highest and second-highest private valuations, and consequently the buyer's profit. Perhaps less intuitively, the buyer's profit is also an increasing function of the valuation uncertainty ($R_v(t)$) associated with the established operations of the target. As the valuation uncertainty increases, each bidder's optimal bid decreases (see the third term in Equation (1)) because each bidder discounts her bid more to account for the familiar winner's curse in common value auctions. Consequently, the buyer's profit from the acquisition increases because of a lower selling price for the target. Finally, the presence of more bidders (n) increases competition and reduces buyer profit.

2.5. Target Age and Profit for the Acquirer
Our primary hypothesis follows immediately from Equation (2). To examine the impact of target age on acquirer profit, we differentiate (2) with respect to target age t, which yields

$$\frac{d\pi_w}{dt} = \pi'_w(t) = \frac{R'_p(t) + R'_v(t)/n}{n+1}. \quad (3)$$

Because $R_p(t)$ and $R_v(t)$ are decreasing functions of target age t, it follows that $R'_p(t) < 0$ and $R'_v(t) < 0$, and consequently $\pi'_w(t) < 0$. Equation (3) illustrates the two mechanisms behind the age effect we hypothesize. As a target becomes older, lower valuation uncertainty ($R_v(t)$) leads to lower bid discounts,

and profit to the winner decreases. Also, as the target becomes older, it develops structural inertia and its technology becomes more mature. Thus, the acquirer has less flexibility ($R_p(t)$) in developing the growth options of the target in unique ways, thereby reducing the distance between the highest and second-highest private valuations, and profit to the winner decreases.

HYPOTHESIS 1 (H1). *In high-technology environments, value captured by the buyer will be negatively associated with target age.*

2.6. Moderators and Boundary Conditions

Equation (3) also allows us to explore conditions that moderate the effect of target age on acquirer profit. Specifically, conditions that reduce the magnitude of $R'_p(t)$ and $R'_v(t)$ in (3) will reduce the impact of target age on acquirer profit ($\pi'_w(t)$). In this section, we investigate the effect of two such conditions—the presence of recent R&D activity in the target and privately held status of the target.

A key difference in some targets lies in the intellectual property they possess, frequently protected through patents. Although the value of a patent is incorporated in the price paid for the target, we argue that recent patents mitigate the negative effects of increased target age. Recent patents signal the presence of research and development activity in the target (Griliches 1990). These activities produce ongoing innovation, reduce concerns about aging and a lack of innovation (Sorensen and Stuart 2000), and indicate unexplored growth options that make an older target more akin to a young company. These unexplored growth options retain flexibility for the buyer for opportunistic evolution and experimentation based on market conditions (McGrath 1997, McGrath and Nerkar 2004, Rindova and Kotha 2001). Thus, the target's flexibility decreases less with age, and $R'_p(t)$ is lower in magnitude (less negative and closer to zero) for targets that have recent patents. Consequently, the magnitude of $\pi'_w(t)$ in (3) decreases.

HYPOTHESIS 2 (H2). *In high-technology environments, recent target patents mitigate the negative effect of target age on value captured by the buyer.*

Another key observable difference is that some targets are public whereas others remain private at the time of acquisition. Prior research has found significant differences between the two subgroups and have documented a direct positive effect of target private status on acquirer value (Faccio et al. 2006, Fuller et al. 2002). Unlike public companies, a privately held target is not required to publicly disclose its financials and business conditions to its investors (Faccio et al. 2006). This raises information acquisition cost for bidders, and the amount of information collected is a decreasing function of this cost (Mantecon 2008).

In addition to limited information disclosure, private targets do not benefit from analyst coverage. Furthermore, there is no public equity price available (Mantecon 2008). Thus, in spite of a longer history of revenues, performance, and profitability, a private target retains more valuation uncertainty for the bidder than a similar age public target. Thus, valuation uncertainty ($R_v(t)$) decreases less with age for private targets because the passage of time reveals less information, $R'_v(t)$ in (3) is lower in magnitude (less negative and closer to 0), and the magnitude of $\pi'_w(t)$ decreases.

HYPOTHESIS 3 (H3). *In high-technology environments, privately held status of the target mitigates the negative effect of the target age on value captured by the buyer.*

2.7. Seller Revenue, Target Age, and Acquisition Probability

Because acquirer profit decreases with target age, why are all target firms not acquired early in their tenure? The timing of the acquisition is also controlled by the seller who agrees to the sale only when the highest bid is over her reservation price. The revenue to the seller is the expected value of the highest bid in the auction. Let w denote the identity of the winning bidder. The seller's revenue, $SR(t)$, for a target of age t is derived directly from (1). As before, $R_s(t) = R_p(t) + R_v(t)/n$:

$$SR(t) = b_w(t) = E[p_w(t) \mid s_w(t) > s_j(t) \ \forall j \neq w]$$
$$+ \overline{V}(t) - \frac{R_s(t)}{n+1}. \quad (4)$$

That is, the seller's revenue is equal to the expected value of the winner's private valuation $p_w(t)$ (given that the winner's value signal $s_w(t)$ is the highest among all bidders), plus the value of the mature operations of the target ($\overline{V}(t)$), minus the amount that a bidder discounts her bid to make a profit. Because the bid discount decreases with target age, $\overline{V}(t)$ increases with target age, and the expected value of the winner's private valuation also decreases with target age, the seller's revenue may be maximized at an intermediate target age.

We assume that a reasonable estimate of the reservation price of the seller at age t is the value of the mature operations of the target ($\overline{V}(t)$) at age t. Clearly, if the highest bid is below this value, the seller should hold on to the target rather than accept the highest bid. Thus, the probability that the target is acquired at age t (provided that the target has not been acquired until that time) is given by

$$P(t) = \Pr[SR(t) - \overline{V}(t) > 0]$$
$$= \Pr\left[p_w(t) > \frac{R_s(t)}{n+1} \ \middle| \ s_w(t) > s_j(t) \ \forall j \neq w\right]. \quad (5)$$

The probability of acquisition at age t is equal to the probability that the bid discount is less than the highest bidder's private valuation of target unexplored growth options. In the appendix, we derive an expression for $P(t)$ and we state it here without proof:

$$P(t) = 1 - \frac{n}{n+1}\left(\frac{R_s(t)}{R_p(t)}\right)$$
$$\cdot \left[\left(\frac{R_s(t)}{n+1} + \frac{R_v(t)}{n}\right)\bigg/\left(R_p(t) + 2\frac{R_v(t)}{n}\right)\right]^{n-1}. \quad (6)$$

In Equation (6), $P(t) = 0$ if the last term in (6) is greater than 1. We also show in the appendix that $P(t)$ is an increasing function of $R_p(t)$ and as decreasing function of $R_v(t)$. The intuition is as follows. As $R_p(t)$ increases, the expected value of the highest bidder's private valuation of unexplored growth options increases, and the highest bid value increases, thereby increasing the probability of acquisition. On the other hand, as $R_v(t)$ increases, bid discounts are higher and bid values are lower, thereby lowering the probability of acquisition.

The structure of $P(t)$ described above allows us to evaluate the impact of two common and observable characteristics of the target. First, consider a target that has independent signals of higher quality such as those from patents, patent citations, and positive analyst coverage (Hsu and Ziedonis 2007). Such signals of high quality reduce valuation uncertainty ($R_v(t)$), decrease bid discounts, and increase the probability of acquisition. On the other hand, conditions that reduce the ability of buyers to create private valuations of unexplored growth options ($R_p(t)$) reduce the probability of acquisition. For example, when a target has alternative access to capital and resources such as through venture capital funding, there are fewer growth options that the target cannot exploit effectively on its own, less opportunity for private valuations by acquirers, and a lower probability of acquisition. Therefore, we hypothesize the following:

HYPOTHESIS 4 (H4) *In high-technology environments,* (a) *target firms with independent signals of higher quality have a higher probability of acquisition, and* (b) *target firms that have superior access to capital and resources have a lower probability of acquisition.*

3. Data and Methodology

3.1. Data Sources
Within the telecommunications industry, firms can be classified as equipment manufacturers (e.g., Cisco) or service providers (e.g., AT&T). Equipment manufacturers make acquisitions to obtain new products and technology, whereas a majority of the acquisitions by service providers are to gain access to new customers, new geographic coverage areas, new licenses, and to achieve economies of scale. To focus on the acquisition of products and technology in a high-velocity industry, we restrict our empirical analysis on acquisitions made by telecommunications equipment manufacturers from 1995 until 2001. This was a period of significant market and technological uncertainty in the telecommunications industry due to emerging standards, growing markets, significant investments, and rapid technological development (Carow et al. 2004, Corrocher et al. 2007).

We constructed our data set from two primary sources, complemented with additional data from several other data sources described later in this section. First, we searched the *Wall Street Journal*, *Business Wire*, *PR Newswire* and *Dow Jones News Service* to identify 249 acquisition announcements by equipment manufacturers (such as Cisco, Lucent, and Nortel) between 1995 and 2001. This data set was further augmented with information from the Securities Data Company (SDC) Mergers and Acquisitions database. First, we checked for any acquisitions by equipment manufacturers in the SDC database during this time period to ensure that no relevant acquisitions were missed from the search for announcements. Additionally, though announced, some acquisitions were later withdrawn. After removing withdrawn acquisitions identified through the SDC database, or those that did not involve a technology or product acquisition, or those for which insufficient market trading data was available, or those for which we could not determine the age of the target (see §3.3), or those for which necessary control covariates were unavailable (see §3.4), 140 acquisitions remained for the analysis. These 140 acquisitions formed the primary data set for analyzing buyer profit from acquisitions.

Second, we used the Thomson ONE Banker database to identify 237 *additional* telecommunication equipment firms that were not acquired, but received some venture capital funding prior to December 2001, were active after January 1995, and had all necessary control variables available (see §3.4). Whereas the acquisition data gives us information about firms that were acquired, the venture capital database expands the sample to include firms that were potential targets for acquisition. Although there may be smaller or privately funded firms that are not present in this database, we believe that this is a representative sample of firms in the telecommunications industry that were either acquired or were potential acquisition targets during the focal time period. This universe of 377 firms (140 firms that were acquired plus 237 that were not acquired during this period) provided the data set for survival analysis (see §4.2) to evaluate factors that affect the likelihood of being acquired, and to also refine the analysis of buyer profits by correcting for sample selection biases.

3.2. Abnormal Returns for the Acquirer

We use standard event study methods (Brown and Warner 1985) to measure gain from acquisitions by examining the abnormal stock market reaction to acquisition announcements by equipment manufacturers in the telecommunications industry. The use of event study methods has three advantages in our context. First, the event study method effectively isolates the impact of the acquisition on the acquiring firm better than aggregate measures based on annually reported accounting data (MacKinlay 1997), particularly when firms make several acquisitions within the same year (Fuller et al. 2002). Second, for acquisitions of early stage targets, immediate impact on accounting indicators may be insignificant or even negative and will depend more on the stage of development of the innovation rather than its future value. Furthermore, intangible values inherent in technology acquisitions (such as intellectual property and knowledge assets) are difficult to value through traditional productivity metrics, whereas equity prices include a capitalization of all future benefits. Third, event studies are well established in the product development (Girotra et al. 2007, Hendricks and Singhal 1997, Kalaignanam et al. 2007) and acquisitions (Faccio et al. 2006) literature as a method for assessing gain through acquisitions and other managerial decisions. Utilizing a metric that has been frequently used in the literature enables us to exploit previous findings in our model.

For the firms that were acquired, we estimate the change in stock price (the abnormal return) for the acquirer attributable to the acquisition announcement by adjusting the stock price changes for market-wide movements (Brown and Warner 1985). Abnormal returns are calculated using the market model, market adjusted return model, and the Fama-French model. For reasons stated below, the market adjusted return model abnormal returns were used in the primary analysis, whereas the market model and Fama-French model abnormal returns were used for robustness checks.

The market model posits a linear relationship between the return on a stock and the return on the market portfolio over a given time period. This relationship is expressed as $r_{i,t} = \alpha_i + \beta_i r_{m,t} + \epsilon_{i,t}$, where $r_{i,t}$ is the return of stock i on day t, $r_{m,t}$ is the return of the market portfolio on day t, α_i is the intercept of the relationship for stock i, β_i is the slope of the relationship for stock i, and $\epsilon_{i,t}$ is the error term for stock i on day t. The term $\beta_i r_{m,t}$ is the return to stock i on day t that can be attributed to market wide movements, whereas $\epsilon_{i,t}$o is the unexplained part of the return that captures the effect of firm specific events on day t. For each firm, we estimate $\hat{\alpha}_i$ and $\hat{\beta}_i$ using ordinary least squares regression over an estimation period of 200 trading days ending 10 days prior to the acquisition announcement, with the equally weighted Center for Research in Security Prices (CRSP) index as a proxy for the market portfolio. A minimum of 40 return observations in the estimation period is required for the estimation procedure. The abnormal return ($A_{i,t}$) for stock i on day t is $A_{i,t} = r_{i,t} - \hat{\alpha}_i - \hat{\beta}_i r_{m,t}$, where $r_{i,t}$ is the actual return on stock i on day t.

Our primary results and discussion are based on the market adjusted return model that is recommended when frequent acquisitions overlap the estimation period used in the market model leading to biased estimates of the market model parameters (Fuller et al. 2002). In the market adjusted return model, the abnormal return ($A_{i,t}$) for stock i on day t is calculated as $A_{i,t} = r_{i,t} - r_{m,t}$. The rationale is that in the absence of any abnormal return, the return for the stock can be predicted by the market return. For short-window event studies, any gain in estimation from including the market model parameters is lost through overlap of other acquisitions during the market model parameter estimation period (Fuller et al. 2002). To summarize the average valuation impact of acquisition announcements on the market value of firms in our sample, we focus on the abnormal returns ($A_{i,t}$) on the event day ($t = 0$). The use of a one day window allows us to isolate the effects of the acquisition announcement (McWilliams and Siegel 1997). We also dropped firms from the sample that had other announcements on the date of the acquisition announcement. Consistent with other research, we use the abnormal returns ($A_{i,0}$) as the dependent variable in the regressions (e.g., Chang 1998).

3.3. Determining the Age of the Target

Unfortunately, the age of the target at the time of acquisition was not readily available through public data sources. To determine the company inception date, several sources were consulted. First, in some cases, the venture capital database contained the firm start dates. In other cases, the press release about the acquisition noted the start date of the target company. Also, news articles profiling the company or company founders sometimes noted the start date. By searching through news archives and company filings, start dates were obtained for 185 of the 249 companies in our original sample. In 47 cases, both the month and year were available; in the remaining 138 cases, only the year was available and the beginning of the year was used to determine target age. For acquired firms, the age of the target at the time of acquisition ranged from two months to 61 years with a mean of 8.4 years.

3.4. Control and Moderator Variables

Because of the vast literature on acquisitions, it is critical to control for known effects on the abnormal returns associated with acquisitions in order to isolate the impact of target age. Four types of control variables were used in the following regressions: buyer characteristics, target characteristics, acquisition characteristics, and environmental characteristics. All monetary values are converted to the January 1995 equivalent using the U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Indices (CPI).

3.4.1. Buyer Characteristics. For buyer characteristics, we incorporated the *total market value* of the buyer immediately prior to the announcement because firm size has been found to influence acquirer valuation (Moeller et al. 2004) and because abnormal returns are expressed as percentages of market value. The buyer market value ranges from US$104 million to US$430 billion with a mean of US$92 billion. The *buyer leverage* (defined as the prior year debt divided by assets) is included to account for possible improvements in managerial decision making due to high leverage and subsequent oversight by the debt providers (Jensen 1986). Buyer leverage ranges from 0.03 to 0.70 with a mean of 0.28. We include the *number of prior acquisitions* that a firm has done at the time of the announcement to control for learning from prior experiences (Hayward 2002). This data is calculated from the SDC database of mergers and acquisitions. The *buyer free cash intensity* (defined as the net income for the prior year minus income taxes minus preferred and common dividends divided by revenue) is included to control for excess free cash leading to low-benefit acquisitions (Jensen 1986) and ranges from −1.25 to 0.44 with a mean of 0.14. Furthermore, we include *buyer R&D intensity* (defined as the expenditure for the prior year on R&D divided by revenue) to control for absorptive capacity (Cohen and Levinthal 1990). Buyer R&D intensity ranges from 0.01 to 0.84 with a mean of 0.15.

3.4.2. Target Characteristics. Next, because private targets accounted for 67% of our sample, we were limited to data that are available for private firms. For target characteristics at the time of acquisition, we use the natural log of the *total number of employees* at the target to control for the target firm size (Sorensen and Stuart 2000). At the time of acquisition, number of target employees range from 17 to 7,800 with a mean of 533. To determine the number of employees, we combined information from the SDC database, news articles about the target, and required filings. Because of the difficulty in accurately determining the number of employees, 28 acquisitions were excluded. For the analysis of acquirer profits, number of target employees was determined for

the acquisition year. For hazard models of the risk of acquisition (see §4.2), we use employee information at all known dates and use linear interpolation to estimate the number of employees during the focal month. The *public/private status* (defined as 1 if the target was private, 0 if public) is included to control for previously documented public versus private direct effects (e.g., Fuller et al. 2002).

To determine if the potential target company held any patents, we consulted data directly available from the U.S. Patent and Trademark Office and created a data set of 3,858 individual patents for the potential target firms including filing date and grant date as well as a detailed list of the patents that cited patents within the data set. Based on this data, we incorporated a *recent patent indicator* variable that was set to 1 if the target held one or more patents during the three years prior to the acquisition and 0 otherwise (Puranam et al. 2006). (Our results are robust to larger and smaller windows of recent patents.) Only 25% of the targets in our sample had a patent within three years of the acquisition. This dichotomous indicator variable provides a good abstraction of the knowledge available to the market at the time of acquisition (Puranam et al. 2006).

To control for the *technical quality* of the target, we include a metric that is based on a normalized measure of the citations received by the patents owned by the target (patent stock), adjusted for the age of the target. In summary, this measure calculates the value of a patent portfolio based on the number of citations a patent in the portfolio received in subsequent years and how recent the patent is. However, this measure has a significant limitation in our sample because the citations of later patents are truncated. We use a procedure detailed in Hall et al. (2005) to extrapolate the number of citations of a patent to a consistent 30 year lag period from the date of issuance. This citation weighted measure is a better indicator of the value of the patent portfolio than many other measures (Hall et al. 2005). Recent research has also found that the patent citation measure is an appropriate measure of firm quality in high-technology industries (Hsu and Ziedonis 2007). To account for the effect of target size on the patent stock measure, we normalize the metric by dividing by the number of employees at the target, to obtain a measure that is uncorrelated with target size. For the analysis of acquirer profits, we calculated the *technical quality* of the target at the time of acquisition; for the hazard analysis of the risk of acquisition, we calculate the metric at the end of each focal month.

To distinguish between *technical quality* and broader name recognition due to media coverage, we incorporate a measure of the *popular visibility* of the target as a control variable. We calculate popular visibility

as the number of mentions in the Factiva database during the six-month period beginning seven months before and ending one month before the acquisition was announced. Again, to reduce correlation with target size measures, we normalize the metric by dividing by the number of target employees.

From the Thomson ONE Banker database, we calculate the total *venture capital funding* that the target received until the time of acquisition, converted to January 1995 equivalents using the CPI. At the time of acquisition, targets had from US$0 to US$110 million in funding with a mean of US$2.1 million. For the hazard models of acquisition risk, we calculate the metric for each month by including all venture funding received up to and including the focal month.

3.4.3. Acquisition Characteristics. Next, we include characteristics of the acquisition as control variables in the model. The *deal value* is included to control for the size of the transaction. The deal values, as reported by the SDC database, range from US$3.1 million to US$36 billion with a mean of US$1.25 billion. Furthermore, the *deal weight* (defined as the ratio of deal value to the buyer market value) is included to control for the impact of the acquisition on the buyer because of the size difference between the buyer and the target (Moeller et al. 2005). A large size difference can impact bargaining and allow the buyer to extract more of the total acquisition value from the target. Acquisition weights range from 0.001% to 220% with a mean of 11.7%. The source of funds for the acquisition (*cash versus stock*) as reported in the SDC database is included to control for the method of payment (Andrade et al. 2001). A few acquisitions were not completely cash or stock. When the payment form was mixed, we coded it based on the largest source of funds used for the transaction.

We further use patent information by collecting the full text of the 159,945 patents held by the target and acquirer firms, and we examined the 1,055,730 citations by buyer and target patents for overlap. For each of the buyer and target patents, we constructed a list of all other patents cited by each focal patent. For each target-acquirer pair, we calculated the sum of the number of target patents cited by any acquirer patent plus the number of acquirer patents cited by any target patent, and we labeled this metric as *cross citations*. This metric captures the degree to which the target and acquirer technologies overlap. Cross citations range from 0 to 1,570 with a mean of 26.4 citations.

3.4.4. Environmental Characteristics. We include a *post-bubble indicator* variable if the acquisition occurred after the technology "bubble" using March 2000 as the cutoff date (Brunnermeier and Nagel 2004). Furthermore, prior research indicates the presence of acquisition waves in many industries and

highlights certain advantages for acquisitions that are made in the early phases of an industry acquisition wave (Carow et al. 2004). Following the procedure in Carow et al. (2004), we identify pre-1996 as the early part of the acquisition wave in the telecommunications industry, and we include an indicator variable (*early mover*) that is set to 1 if the acquisition occurred prior to 1996.

4. Results and Discussion

4.1. Abnormal Returns

Summarized descriptive statistics and correlations for some of the variables in our analysis are shown in Table 1. Table 2 shows the market adjusted and market model abnormal returns in the whole sample of 140 firms (panel A) and specific subsamples (panels B and C). The results in panel A are consistent with earlier results in the literature and exhibit a strong negative abnormal return from acquisition announcements. The mean market adjusted abnormal return in panel A is −1.18% for day 0, and the *t*-statistics and generalized signed rank test statistic are significant. Interestingly, panels B and C in Table 2 show that the day 0 abnormal returns are muted for younger targets (−0.55% and not significant), and more negative for older targets (−1.81% and significant), indicating preliminary support for H1.

4.2. Hazard Analysis of the Risk of Acquisition

Because not all telecommunications equipment providers are acquired, there is the potential that subsequent analysis of buyer profit from acquisition is biased by sample selection. Therefore, we first examine the risk of a potential target being acquired through a Cox proportional hazard model (Cox 1972) to identify factors that affect the risk of acquisition. We then use these factors in the first stage of the Heckman two-stage regressions with buyer profits as the dependent variable to correct for possible sample selection biases.

In the hazard model, the event being explained is the acquisition of the target firm by a buyer. The Cox proportional hazard model allows us to integrate information about potential targets in our data set that were part of the telecommunications industry but were never acquired, and to handle truncation errors caused by the end of the study period. To perform this analysis, we construct a data set that contains for each potential target firm, a monthly observation of the target and environmental characteristics. (Acquirer and deal characteristics are not applicable.) This results in 20,057 monthly observations for the 377 potential target firms in our sample. The Cox proportional hazard model consists of two parts: the baseline hazard function describing how the risk of acquisition changes

Table 1   Descriptive Statistics and Pearson Product Moment Correlations Between Variables

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. *buyer market value* (US$ × 10^{12})	0.0917	0.1152	1.000																
2. *buyer leverage* (debt/assets)	0.2795	0.1423	−0.030	1.000															
3. *buyer acq. exp.* (ln of no. of prior acqs.)	2.4607	1.6628	0.685	0.149	1.000														
4. *buyer free cash intensity* (free cash/sales)	0.1397	0.1910	0.252	−0.089	0.388	1.000													
5. *buyer R&D intensity* (R&D/sales)	0.1547	0.0972	0.044	−0.202	−0.064	−0.321	1.000												
6. *early mover* (1 if before 1/1996)	0.0429	0.2033	−0.152	0.055	−0.090	0.038	−0.143	1.000											
7. *post bubble* (1 if after 3/2000)	0.3500	0.4787	0.293	−0.125	0.139	−0.072	0.190	−0.155	1.000										
8. *deal value* (ln US$ × 10^9)	5.8935	1.4312	0.055	0.223	−0.010	−0.071	0.161	−0.055	−0.014	1.000									
9. *payment method* (1 if stock, 0 if cash)	0.7357	0.4425	0.019	−0.093	−0.071	−0.067	0.248	0.127	0.100	0.203	1.000								
10. *target age* (In of years)	1.6691	0.9810	−0.109	0.220	−0.073	−0.057	−0.093	0.122	−0.073	0.201	−0.131	1.000							
11. *deal weight* (target size/buyer size)	0.0002	0.0003	−0.282	−0.016	−0.379	−0.328	0.019	−0.001	−0.138	0.305	−0.025	0.239	1.000						
12. *cross citations* (In of count)	0.9762	1.6454	−0.024	0.048	0.167	0.130	−0.023	0.092	−0.160	0.370	−0.130	0.361	0.108	1.000					
13. *Factiva visibility* (mentions/emp.)	1.3489	1.9850	0.043	−0.069	0.066	0.085	−0.023	0.163	−0.064	−0.040	−0.167	−0.075	−0.071	0.158	1.000				
14. *venture capital funding* (In million US$)	0.2501	0.8354	−0.042	0.049	0.023	−0.048	−0.045	0.057	0.032	0.101	0.066	−0.033	−0.029	0.044	0.079	1.000			
15. *technical quality* (In cite weight/emp.)	0.4296	0.4821	−0.127	0.128	−0.038	−0.002	−0.090	0.186	−0.177	0.285	−0.209	0.306	0.113	0.745	0.240	0.100	1.000		
16. *target employees* (In of employee count)	5.1627	1.3048	−0.124	0.267	−0.169	−0.090	−0.081	0.012	−0.144	0.536	−0.146	0.678	0.458	0.405	−0.199	−0.011	0.311	1.000	
17. *target private* (1 if private)	0.6643	0.4740	0.091	−0.145	0.130	0.088	0.041	−0.148	0.141	−0.388	0.088	−0.489	−0.324	−0.468	−0.097	−0.142	−0.482	−0.637	1.000
18. *target recent patent* (1 if has recent patent)	0.1571	0.3652	−0.152	−0.041	−0.155	−0.018	−0.077	0.102	0.012	0.017	0.081	−0.095	−0.020	0.040	0.038	0.025	0.260	−0.064	0.016

Note. Sample size for the above correlations is 140 and includes the firms for which we had abnormal returns and values for all control variables.

Table 2   Cumulative Buyer Abnormal Returns for the Whole Sample and Age Subsamples

	Market model				Market adjusted return			
	Days −1 to 1	Days −1 to 0	Days 0 to 0	Days 0 to 1	Days −1 to 1	Days −1 to 0	Days 0 to 0	Days 0 to 1
	Panel A: Whole sample of 140 acquisition announcements							
Mean abnormal return (%)	−1.16	−1.14	−1.18	−1.20	−0.58	−0.62	−1.01	−0.97
Patell *Z*-statistic	−2.253**	−2.899***	−4.313***	−2.910***	−1.107	−1.853**	−3.887***	−2.251**
Signed *Z*-statistic	−0.048	−0.218	−1.910**	−1.572*	0.960	0.115	−1.914**	−1.069
	Panel B: Sample of 70 acquisitions where target age is below median (younger targets)							
Mean abnormal return (%)	−0.01	−0.30	−0.55	−0.26	0.41	0.01	−0.38	0.02
Patell *Z*-statistic	0.122	−0.093	−0.933	−0.418	0.896	0.407	−0.568	0.288
Signed *Z*-statistic	−0.509	0.209	−0.988	−0.270	1.773**	0.817	−0.379	0.817
	Panel C: Sample of 70 acquisitions where target age is above median (older targets)							
Mean abnormal return (%)	−2.30	−1.99	−1.81	−2.13	−1.56	−1.25	−1.65	−1.97
Patell *Z*-statistic	−3.308***	−4.007***	−5.166***	−3.697***	−2.461**	−3.028**	−4.929***	−3.471***
Signed *Z*-statistic	0.441	−0.517	−1.714**	−1.953**	−0.416	−0.655**	−2.328***	−2.328***

Notes. The *t*-statistic is portfolio time series *t*; signed *Z*-statistic is the generalized signed *Z*-statistic.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$ (one-tailed significance).

over time when covariates are at the mean level; and a parameter for each covariate that describes how the baseline hazard changes in response to explanatory covariates. In the Cox model, the baseline hazard is not affected by the covariates, and the parameters are assumed to have a multiplicative effect on the baseline hazard. To incorporate unobserved heterogeneity in target specific risk, we include shared frailty by potential targets.

Table 3 describes the results related to the probability of acquisition based on the Cox proportional hazard model. The table demonstrates that higher technical quality of the target (as measured through the patent citation variable described earlier) increases

Table 3   Cox Proportional Hazard Model Estimates of the Risk of Acquisition

Variable	Model 1	Model 2	Model 3	Model 4
β_1 early mover (1 if before 1/1996)	−3.899*** (0.009)	−3.957*** (0.009)	−3.885*** (0.010)	−3.926*** (0.009)
β_2 post bubble (1 if after 3/2000)	0.105 (0.200)	0.588** (0.332)	0.084 (0.196)	0.604** (0.337)
β_3 target employees (ln)	0.298*** (0.132)	0.257* (0.135)	0.303*** (0.135)	0.244* (0.135)
β_4 target venture funding (ln)		−1.323*** (0.049)		−1.332*** (0.048)
β_5 target technical quality (ln)			0.145*** (0.085)	0.206*** (0.090)
Pseudo R^2 (%)	15.54	22.51	15.78	22.99
Wald χ^2	76.913***	139.037***	84.640***	156.502***
Log-likelihood	−641.482	−588.511	−639.630	−584.905

Notes. Cox proportional hazard estimates on 20,057 monthly observations of 377 firms. Failure is acquisition; all continuous variables are standardized.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$ (two-tailed significance).

the likelihood of acquisition, and our results support H4(a). Furthermore, we find that venture capital funding decreases the likelihood of acquisition as firms have capital to operate without being acquired. Our results support H4(b). In addition, the likelihood of acquisition increases marginally with firm size. We also see that during the early mover time period (pre-1996), acquisitions were much less likely to occur. During this time period, high levels of valuation uncertainty lead to higher bid discounts, lowering the probability that the highest bid will be above the reservation price of the seller. After the Internet bubble, firms were more likely to be acquired, because lower reservation prices of sellers increase the likelihood of acquisition. Overall, in terms of target characteristics, the results from the Cox proportional hazard model support the use of target employees, venture capital funding, and technical quality as explanatory variables in the first stage of the Heckman two-stage regressions that we describe next.

4.3. Cross-Sectional Regression Analysis

To evaluate H1–H3, abnormal returns were analyzed using two-stage selection models. Table 4 shows the results with the market adjusted model, market model and Fama-French model abnormal returns. All regressions use the single day (day 0) abnormal return as the dependent variable and all models provide consistent results. However, as suggested by Fuller et al. (2002), because of the presence of acquirers with multiple acquisitions that have overlapping estimation periods, we focus on the results that are based on the market adjusted model abnormal returns in Table 4. All continuous variables are standardized by

Table 4   Heckman Regression on Day 0 Market Adjusted, Market Model (MM), and Fama-French (FF) Returns

Variable	Model 1	Model 2	Model 3	Model 4	MM	FF
β_0 Intercept	−0.896	−0.414	3.742*	5.805***	5.780***	6.387***
	(1.116)	(1.129)	(1.994)	(2.013)	(1.901)	(1.624)
β_1 buyer market value	0.501	0.443	0.296	−0.218	−0.083	−0.208
(US$)	(0.528)	(0.541)	(0.617)	(0.619)	(0.494)	(0.419)
β_2 buyer leverage	0.303	0.384	0.279	0.002	0.067	0.037
(debt/assets)	(0.545)	(0.531)	(0.557)	(0.562)	(0.473)	(0.450)
β_3 buyer acquisition experience	−0.211	−0.254	−0.764	−0.366	−0.313	−0.158
(ln of prior acquisitions)	(0.708)	(0.656)	(0.601)	(0.527)	(0.505)	(0.467)
β_4 buyer free cash intensity	−0.293	−0.447	−0.488	−0.649	−0.741	−0.465
(free cash/sales)	(0.619)	(0.526)	(0.594)	(0.691)	(0.657)	(0.547)
β_5 buyer R&D intensity	−0.390	−0.468	−0.494	−0.069	−0.175	−0.069
(R&D/sales)	(0.670)	(0.607)	(0.698)	(0.805)	(0.821)	(0.667)
β_6 early mover (pre-1996)	−0.030	0.793	0.239	0.916	0.730	0.863
(1 if yes, 0 if no)	(1.579)	(1.494)	(1.530)	(1.896)	(1.726)	(1.462)
β_7 post bubble (post–March 2000)	0.920	1.041	1.413	1.926*	1.385	1.800**
(1 if yes, 0 if no)	(1.112)	(1.126)	(1.064)	(1.164)	(0.935)	(0.897)
β_8 acquisition value	−1.085**	−0.770	−0.345	−0.285	−0.355	−0.449
(ln US$)	(0.538)	(0.522)	(0.709)	(0.680)	(0.656)	(0.643)
β_9 payment method	0.284	−0.377	−0.020	0.324	0.114	−0.138
(1 if stock, 0 if cash)	(0.834)	(0.780)	(0.875)	(0.943)	(0.761)	(0.681)
β_{10} target age		−1.239**	−1.224	−3.982***	−3.579***	−3.656***
(ln of years)		(0.597)	(1.131)	(0.950)	(0.916)	(0.921)
β_{11} acquisition weight			−0.555	−0.442	−0.460	−0.321
(acq. val./buyer val.)			(0.500)	(0.422)	(0.466)	(0.526)
β_{12} cross citations			0.336	0.282	0.400	0.183
(ln)			(0.554)	(0.651)	(0.622)	(0.548)
β_{13} target popular visibility			0.086	0.120	−0.027	−0.226
(Factiva/employees)			(0.374)	(0.400)	(0.364)	(0.379)
β_{14} target venture capital funding			3.524**	4.389***	4.235***	3.946***
(ln US$)			(1.730)	(1.699)	(1.483)	(1.354)
β_{15} target technical quality			−0.979	−0.861	−1.117	−0.706
(ln patent citations/employees)			(0.904)	(0.998)	(0.928)	(0.840)
β_{16} target employees			0.216	0.500	0.310	0.211
(ln)			(1.189)	(1.033)	(1.003)	(0.967)
β_{17} target private			0.972	0.704	0.141	−0.697
(1 if yes, 0 if no)			(1.602)	(1.493)	(1.413)	(1.384)
β_{18} target recent patent			−0.028	−0.297	0.376	−0.327
(1 if yes, 0 if no)			(1.463)	(1.383)	(1.215)	(1.034)
β_{19} recent patent × target age				2.400**	2.487**	1.785
				(1.176)	(1.259)	(1.102)
β_{20} private × target age				3.800***	3.304***	3.529***
				(1.198)	(1.094)	(1.063)
Selection stage						
β_0 intercept	−0.558***	−0.557***	−0.558***	−0.565***	−0.568***	−0.568***
	(0.103)	(0.102)	(0.100)	(0.098)	(0.098)	(0.098)
β_1 target employees	−0.037	−0.032	−0.021	−0.024	−0.019	−0.019
(ln)	(0.083)	(0.080)	(0.075)	(0.071)	(0.072)	(0.071)
β_2 target technical quality	0.296***	0.299***	0.273***	0.272***	0.261***	0.253***
(ln patent citations/employees)	(0.092)	(0.092)	(0.093)	(0.090)	(0.088)	(0.087)
β_3 target venture capital funding	−1.095***	−1.092***	−1.049***	−1.015***	−1.023***	−1.017***
(ln US$)	(0.141)	(0.139)	(0.143)	(0.139)	(0.137)	(0.138)
χ^2	8.260	16.105	26.614	51.050	51.406	55.390
Log likelihood	−605.642	−602.849	−600.070	−592.505	−588.693	−584.414

Notes. Robust errors are in parentheses. $n = 365$; continuous variables are standardized.
    *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$ (two-tailed significance).

subtracting the mean of the variable and dividing by its standard deviation, to reduce potential multi-collinearity effects when interaction terms are present, to make the constant term more meaningful, and to make the coefficients comparable (Aiken and West 1991). We utilized Heckman two-stage regression with robust estimation of standard errors to adjust param-eter estimates by accounting for the probability of acquisition in the first stage.

The first (selection) stage shown at the bottom of Table 4 is consistent across all models. Consistent with the hazard analysis in Table 3, venture capital fund-ing decreases the likelihood of acquisition (Table 4 model 4, $\beta = -1.015$, $p < 0.01$). As an indicator of

firm quality, target technical quality increases the likelihood of acquisition (Table 4 model 4, $\beta = 0.2718$, $p < 0.01$). Firm size (number of employees) does not influence the likelihood of acquisition and its coefficient is not significant.

In model 1, all control variables that are unrelated to target characteristics were included in stage 2 of the Heckman two-stage analysis. Then, in model 2, the age of the target (using a natural log transformation) was entered in the regression model. Consistent with H1, the coefficient for target age ($\beta = -1.239$, $p < 0.05$) is negative and significant. The results indicate that for every standard deviation increase in target age, the abnormal return decreases by 1% of buyer market value. Because the average day 0 abnormal return is around -1%, the impact of target age is economically significant. In model 3, the control variables related to target characteristics are entered in the regression model, and the coefficient for target age is still negative, but no longer significant ($\beta = -1.224$). We conclude from Table 2 (panels B and C) and Table 4 that target age negatively affects abnormal returns for the buyer, but it may be a proxy for other characteristics of the target.

In model 4, we present the results for the complete model that provide strong support for H2 and H3. The coefficient for target age in model 4 is negative and significant ($\beta = -3.982$, $p < 0.01$), indicating that for every standard deviation increase in target age for a public company that does not have recent patents, there is a fourfold decrease in abnormal return for the buyer. The coefficient for the target recent patent indicator variable is not significant, indicating that the value of target recent patents is incorporated in the selling price of the target. Additionally, consistent with H2, the interaction of target age with the recent patent indicator variable is positive and significant ($\beta = 2.400$, $p < 0.01$), indicating that recent target patents reduce the negative impact of target age on abnormal returns.

Contrary to expectations and previous research (Faccio et al. 2006, Officer 2007), the coefficient for the private indicator variable is positive but not significant in model 4, suggesting that there is no direct effect of private status of the target on abnormal returns for the buyer. However, consistent with H3, the interaction between target age and target private status is positive and significant ($\beta = 3.800$, $p < 0.01$), indicating that private status of the target reduces the negative impact of target age on abnormal returns for the buyer.

Examining the control variables in the model, we find that the post-bubble indicator is positive and marginally significant ($\beta = 1.926$, $p < 0.1$). After the Internet bubble, reservation price of targets decreased significantly, leading to lower prices and higher abnormal returns for the buyer. Somewhat surprisingly, we also find that the presence of venture capital funding increases buyer abnormal returns, even though such targets are likely to have higher reservation prices. Perhaps, the presence of venture capital funding is interpreted by the equity markets as an indication of target quality, leading to higher abnormal returns. The cross-citations metric is positive but not significant in the results.

4.4. Summary of Results
Overall, target age has a negative and marginally significant effect on abnormal returns for the buyer in the whole sample. However, consistent with Hypotheses 2–3, the negative impact of target age is most pronounced in two subgroups: targets without recent patents and public targets. Because the effect of target age is muted for private targets and targets with recent patents, the effect of target age in the overall sample will depend on the number of such targets in the sample.

The results from the Cox proportional hazard model in Table 3 indicate that the probability of acquisition increases for targets that have independent signals of higher quality as measured through the citation of patents held by the target. Signals of higher quality decrease the valuation uncertainty associated with a target, increasing bid values, and increasing the probability that the winning bid is higher than the reservation price of the target. Additionally, targets that have superior access to capital and resources, as measured through the amount of venture capital funding received by the target, have a lower probability of acquisition because the acquirer has less opportunity for synergistic private valuations.

5. Summary and Implications

5.1. Reasons Behind the Age Effect in Technology Acquisitions
Our analytical model identifies two underlying reasons behind the age effect: (a) unexplored growth options in young targets provide flexibility and greater opportunities for private synergistic value, and (b) valuation uncertainty of young targets leads to lower bids and a lower selling price. Our empirical analysis provides support for these underlying causes of the age effect by demonstrating: (a) that when a target has growth options irrespective of age such as through recent patents, the negative effect of target age is reduced, and (b) that when a target remains privately held, thereby retaining valuation uncertainty irrespective of age, the negative effect of target age is reduced.

5.2. The Importance of Financial Variables

Beyond the main findings of the research outlined above, our empirical results also provide another interesting insight. None of the financial variables in the model are significant in the regression results in Table 4. Empirical research on acquisitions in other industries has consistently demonstrated lower acquirer returns when equity is used to finance the transaction (Shleifer and Vishny 2003). However, this variable is not significant in any of the regression models. Furthermore, in contrast to earlier findings (Andrade et al. 2001), the variables related to free cash flow and debt are also not significant. The variables that are significant in the model are related to target patent ownership, target age, and private status. Overall, our results indicate that the drivers of acquisitions in the high-technology industries are not captured through the traditional finance variables, emphasizing the need for a fresh perspective.

5.3. Limitations and Boundary Conditions

It is also important to emphasize several limitations of this study that indicate opportunities for future research. The theoretical model utilized in the paper to motivate the hypotheses is static in nature and does not model the seller's best response and her optimal time to sell. Likewise, the amounts bid by potential buyers will be affected by their expectations of the future, and our static model does not capture this dynamic response. Whereas the focus of this research has been on the empirical analysis, future research can extend the analytical model to incorporate the buyer's and seller's best response through a dynamic framework that simultaneously and endogenously determines the optimal reservation price set by the seller and the optimal bid by the buyer at each target age. Further, although event study methods utilized in this research demonstrate the advantages of acquiring early, market evaluations are imperfect measures of true value, even in efficient markets. Thus, it remains to be seen if the advantages of acquiring early translate to long-term and sustainable competitive advantage. The use of detailed accounting or survey data on long-term acquisition performance will provide additional insights. Furthermore, we investigated two important reasons behind the age affect through our analysis, and it is certainly possible that there are other reasons not explored in this paper. For example, although we have partially controlled for target quality through the patent citation metric, it is possible that unobserved target quality differences may drive some of the results. Likewise, we have provided an explanation for our recent patent and private status interactions based on the primitives of our model, but there can be additional explanations for the results. For example, the decision to patent and to remain private are treated as exogenous in the model, whereas they can be strategic choices made by a target for maximizing the value from subsequent acquisitions. Furthermore, despite the selection models, there may be residual sample selection biases because we are constrained to those acquisitions that are publicly announced and for which we have data for all variables in the model.

Our data is limited to acquisitions made by equipment manufacturers within the telecommunications industry. Although the single industry focus has advantages, it also behooves us to analyze the boundary conditions of our findings. The rationale for the hypotheses examined here is rooted in two fundamental assumptions. First, our analytical model assumes a competitive market environment where there are multiple buyers for a target and the acquisition process can be reasonably approximated by a first-price auction. That was the situation in the communications equipment industry during the time period of the study because there was an active market for acquisitions, many acquiring firms had raised capital from the equity markets to fund their acquisitions, and many equipment manufacturers looked to supplement their internal R&D through an active acquisition program. Second, our analytical model is based on the technical and market uncertainties prevalent in some environments. Conditions that foster technical uncertainties include a high rate of technological innovation and emerging standards. Conditions that foster market uncertainties include time-to-market pressures, unpredictable demand, and hypercompetitive environments with multiple players. In summary, the convergence of uncertainties and an active acquisition market creates a high-velocity environment where the benefits of acting quickly outweigh the risks of such action. It is to such environments that may evolve in other industries at later times that our results can be extended.

Appendix. Optimal Bids, Buyer Profits and Acquisition Probability

A.1. Combining the Private and Common Value Signals

At the time of making a bid, a bidder has two signals of value ($v_i(t)$ and $p_i(t)$) for the mature operations (v_i) and growth options (p_i) of the target at age t. Thus, her current estimate of value is $v_i(t) + p_i(t)$, but that may not be the optimal bid due to the well known "winner's curse" in common value auctions (Milgrom 1989). In general, combining multiple signals into a single combined signal that can be used to determine optimal bids is a difficult problem (Milgrom 1989). However, when the best estimate of the common

value portion (V) is the average of the common value signals of all bidders ($V = \sum_{\forall i} v_i(t)$), the combined metric ($s_i(t)$) on which optimal bids can be formulated is given by $s_i(t) = p_i(t) + v_i(t)/n$, where n is the number of bidders (Goeree and Offerman 2002, 2003).

The logic based on Goeree and Offerman (2002) is as follows: If b_i is her bid, then bidder i's expected profit is: $(p_i(t) + v_i(t)/n + \sum_{j \neq i} v_j(t)/n - b_i) \times$ probability that bidder i wins the auction with her bid. At the time of making the bid, bidder i only knows her p_i and v_i values, and not those of other bidders. Thus, the first-order conditions will determine the optimal bid b_i as a function of $s_i(t) = p_i(t) + v_i(t)/n$, because all other terms are unknown to the bidder at the time of the bid.

A.2. Optimal Bids

The derivation of optimal bids is based on ideas presented in Goeree and Offerman (2002) on combined private and common value auctions. We assume that optimal bids are increasing in the combined signal $s_i(t)$ for all bidders i. At the time of making the bid, bidder i knows her private and common value signals (p_i and v_i) and the number of potential bidders (n). In addition, bidder i knows the magnitude of the range ($R_v(t)$) of the uniform distribution from which the common value signals are drawn (indicating the uncertainty associated with the valuation of the established operations of the target). Bidder i also knows the magnitude of the range ($R_p(t)$) of the uniform distribution from which the private value signals are drawn (indicating the potential for value creation through synergistic fit of the target with acquirers). Thus, the combined signals $s_i(t)$ are uniformly distributed with range $R_s(t) = R_p(t) + R_v(t)/n$.

Let $b(s_j(t))$ denote the function that determines optimal bids given a combined signal $s_j(t)$ for all bidders $j \neq i$. To determine the symmetric Bayesian-Nash equilibrium bids, we proceed in the following manner (Krishna 2002). For bidder i, assume that she bids $b(z_i)$ when her combined signal is $s_i(t)$ (instead of bidding $b(s_i(t))$ like all others). Her expected profit (π_i) at the time of bidding is

$$\pi_i = \left(s_i(t) + E\left[\sum_{j \neq i} \frac{v_j(t)}{n} \,\middle|\, s_i(t) > s_j(t) \; \forall j \neq i \right] - b(z_i) \right)$$
$$\times \left(F_s(z_i \mid s_i(t) > s_j(t) \; \forall j \neq i) \right)^{n-1}, \tag{7}$$

where F_s is the cumulative distribution function for all s_j. In the right-hand side of Equation (7), the first term is the expected profit for bidder i if she wins the auction with bid $b(z_i)$, and the second term is the probability that she wins the auction (z_i is greater than the signals $s_j(t)$ for all other $n-1$ bidders). Note that the expected value in the first term of the right-hand side and the F_s function are calculated assuming that bidder i has the highest combined signal (i.e., $s_i(t) > s_j(t) \; \forall j \neq i$) to avoid the familiar winner's curse in common value auctions (McAfee and McMillan 1987). To obtain the symmetric Bayesian-Nash equilibrium bid, we differentiate π_i with respect to z_i, and evaluate the first-order condition ($\partial \pi_i / \partial z_i = 0$) at $z_i = s_i(t)$. We obtain the

following optimal bid for bidder i (note that ($\partial F_s(x)/\partial x = f_s(x) = 1/R_s$) for a uniform distribution:

$$b(s_i(t)) = s_i(t) + E\left[\sum_{j \neq i} \frac{v_j(t)}{n} \,\middle|\, s_i(t) > s_j(t) \; \forall j \neq i \right]$$
$$- \left(\frac{R_s(t)}{n-1} \right) \times F_s(s_i(t)) \times b'(s_i(t)), \tag{8}$$

where $F_s(s_i(t))$ is the cumulative distribution function for the combined signals s_i (for concise presentation we have dropped the condition statement from the function). Because the right-hand side of Equation (8) includes $b'(s_i(t))$, we need an expression for $b'(s_i(t))$. Differentiating both sides of (8) with respect to $s_i(t)$, we obtain

$$b'(s_i(t)) = 1 - \frac{b'(s_i(t))}{n-1} + b''(s_i(t)) \frac{R_s(t) \times F_s(s_i(t))}{(n-1)}.$$

To search for optimal linear bid functions first, we set $b''(s_i(t)) = 0$ and we obtain $b'(s_i(t)) = (n-1)/n$. Furthermore, let V represent the best estimate of the common value portion of the target ($V = \sum_{\forall j} v_j(t)/n$). Substituting in Equation (9), we obtain the following:

$$b(s_i(t)) = p_i(t) + E[V \mid s_i(t) > s_j(t) \; \forall j \neq i]$$
$$- \left(\frac{R_s(t)}{n} \right) \times F_s(s_i(t)). \tag{9}$$

The first two terms in (9) represents the expected value of the target to the bidder if she wins the auction, and the third term is the amount by which she shaves her bid to make a profit. Also, $F_s(s_i(t) \mid s_i(t) > s_j(t) \; \forall j \neq i) = n/(n+1)$, because each bidder i assumes her combined signal $s_i(t)$ to be the highest among n bidders while making the bid (McAfee and McMillan 1987):

$$b(s_i(t)) = p_i(t) + E[V \mid s_i(t) > s_j(t) \; \forall j \neq i] - \frac{R_s(t)}{n+1}. \tag{10}$$

Equation (10) is the same as (1) in the paper. Equation (10) indicates that the Nash equilibrium bidding strategy is one where each bidder bids the expected value of the target assuming that her signal is the highest, minus an amount that is equal to the expected difference between the highest and second-highest combined signals. It follows easily that the profit to the buyer (w) is

$$\pi_w(t) = \frac{R_s(t)}{n+1} = \frac{R_p(t) + R_v(t)/n}{n+1}. \tag{11}$$

Equation (11) is the same as (2) in the paper and matches Proposition 1 in Goeree and Offerman (2003, p. 628).

A.3. Probability of Acquisition

From §2.7, the probability that the target is acquired at age t (provided that the target has not been acquired until that time) is given by

$$P(t) = \Pr\left[p_w(t) > \frac{R_s(t)}{n+1} \,\middle|\, s_w(t) > s_j(t) \; \forall j \neq w \right]. \tag{12}$$

That is, the probability of acquisition at age t is equal to the probability that the bid discount is less than the highest bidder's private valuation of target growth options. We first

derive an expression for $P(t)$ and then we show that $P(t)$ is a decreasing function of $R_v(t)$ and an increasing function of $R_p(t)$. Using Bayes' Theorem,

$$
\begin{aligned}
P(t) &= 1 - \Pr\left[p_w(t) < \frac{R_s(t)}{n+1} \,\bigg|\, p_w(t) > s_j(t) - \frac{v_w(t)}{n} \;\forall j \neq w \right] \\
&= 1 - (\Pr[s_j(t) - v_w(t)/n < p_w(t) \;\forall j \neq w \,|\, p_w(t) < R_s(t)/(n+1)] \\
&\quad \times \Pr[p_w(t) < R_s(t)/(n+1)])(\Pr[s_w(t) > s_j(t) \;\forall j \neq w])^{-1} \\
&= 1 - \frac{\Pr[s_j(t) - v_w(t)/n < R_s(t)/(n+1)]^{n-1} \times \Pr[p_w(t) < R_s(t)/(n+1)]}{\Pr[s_w(t) > s_j(t) \;\forall j \neq w]}.
\end{aligned}
$$

Now, $s_j(t) - v_w(t)/n$ is a random variable that is distributed uniformly with range $R_s(t) + R_v(t)/n = R_p(t) + 2R_v(t)/n$. The denominator (probability that w has the highest signal among n bidders) is $1/n$. Using the cumulative distribution functions for the uniform distribution, we obtain

$$
\begin{aligned}
P(t) = 1 &- \frac{n}{n+1}\left(\frac{R_s(t)}{R_p(t)}\right) \\
&\cdot \left[\left(\frac{R_s(t)}{n+1} + \frac{R_v(t)}{n}\right)\bigg/\left(R_p(t) + 2\frac{R_v(t)}{n}\right)\right]^{n-1}. \quad (13)
\end{aligned}
$$

The partial differential of $P(t)$ with respect to $R_p(t)$ and $R_v(t)$ is given below:

$$
\begin{aligned}
\frac{\partial P(t)}{\partial R_p(t)} &= \frac{n^2(n^2 - n + 1)R_p^2 R_v + n(n^2 + 4)R_p R_v^2 + 2(n+2)R_v^3}{R_p^2(2R_v + nR_p + nR_v)^2} \\
&\quad \cdot \left(\frac{(2R_v + nR_p + nR_v)}{(n+1)(nR_p + 2R_v)}\right), \quad (14)
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial P(t)}{\partial R_v(t)} &= -\frac{n^2(n^2 - n + 1)R_p^2 + n(n^2 + 4)R_p R_v + 2(n+2)R_v^2}{R_p(2R_v + nR_p + nR_v)^2} \\
&\quad \cdot \left(\frac{(2R_v + nR_p + nR_v)}{(n+1)(nR_p + 2R_v)}\right). \quad (15)
\end{aligned}
$$

Clearly, $\partial P(t)/\partial R_p(t) > 0$ and $\partial P(t)/\partial R_v(t) < 0$. Thus, $P(t)$ is a decreasing function of $R_v(t)$ and an increasing function of $R_p(t)$.

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