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ORIGINAL EMPIRICAL RESEARCH

The dynamic nature of survival determinants in e-commerce

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Abstract The dynamic effects of survival determinants in e-commerce are tested using longitudinal data on 460 e-tailers. This is achieved through the incorporation of both time-varying covariates and coefficients in a discrete hazard rate model. The model includes elements of competitive strategy, industry structure, firm and product characteristics, and the macro environment. The study demonstrates the changing effect over time of factors affecting survival. For example, order of entry advantages are observed, but they are short-lived. This finding shows that e-tailers cannot rely on early entry as a strategic move in the long run. E-tailers with more media presence seem to survive longer. Being publicly traded and selling products with digital characteristics present advantages for e-tailers only in the beginning years, but they are not sustainable over long time periods. Survival chances decrease with higher competitive density, market growth rate, and equity market level at the time of entry. Conversely, economic growth tends to increase survival chances. The study also finds an inverted-U relationship between the hazard of exit and firm age. The conclusion section discusses the implications of the time-varying nature of survival determinants.

Keywords Survival analysis · Order of entry · Online retailing · Time-varying effects

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Introduction

It is important to study the evolution of an industry for several reasons. First, it is essential for managers to know at what stage they join the industry, because this will impact their marketing strategies. For example, a growing industry is more turbulent and risky than a mature one. Second, if managers recognize the effect of certain survival determinants, they can plan better strategies for exit or exit avoidance. For example, more vulnerable firms with unique offerings can seek alliances with bigger companies. Or they can purposefully delay their entry until after the turbulent period in the industry and find a favorable niche in the market. Third, managers need to be aware of the time-varying nature of factors affecting their strategy. A beneficial aspect of the initial entry strategy might diminish its effect over time. Conversely, overcoming some obstacles in the introductory stage may have positive returns in later stages. This calls for an evolutionary perspective on survival determinants.

Most of the existing industry evolution studies examine the static nature of survival determinants (e.g. Agarwal, 1997; Nikolaeva, Kalwani, Robinson & Sriram, 2006). One exception is a study by Agarwal, Sarkar, and Echambadi (2002) looking at contemporaneous effects of survival determinants. In addition, while the concept of strategizing according to the different stages of the product life cycle has been accepted as a basic postulate in marketing, the time-varying nature of survival determinants has been largely ignored in the literature.

Filling this gap, the current study investigates important survival determinants in the online retailing setting (Mahajan, Srinivasan, & Wind 2002; Nikolaeva et al., 2006) using population ecology tools. It is based on a longitudinal database of 460 e-tailers examining their entry and possible exit through September 2003. The study employs duration models to estimate how Varadarajan and Yadav's (2002) framework elements of competitive strategy, industry structure, firm characteristics, product characteristics, and the macro environment influence e-tailer survival and how these effects change over time. In summary, the contributions of the paper are these:

1. The study provides an empirical test of Varadarajan and Yadav's (2002) theoretical framework for Internet integration into marketing strategy.
2. It tests the *dynamic* nature of factors affecting firms' survival in a duration modeling framework. This allows for the testing of the time-varying nature of both covariates and coefficients—a new approach in the marketing literature.
3. It fills a gap in the order of entry literature by tracing the order of entry effect over time. Further, the study is conducted in a service industry using hazard rate methodology, which answers a call by Lieberman and Montgomery (1998) of enriching the order of entry literature.

Theoretical framework

Varadarajan and Yadav (2002) propose a theoretical framework for integrating the Internet into marketing strategy. They describe how various drivers and outcomes of competitive strategy change with the advent of the Internet in business strategies. This theoretical framework is applied to the online retailing setting to explore the dynamic nature of firm survival drivers. Based on it, business performance depends on competitive strategy, industry, firm, product, and buyer characteristics. The current study employs the following factors to investigate e-tailer survival: competitive strategy—order of entry, distribution channels, and publicity; industry structure—number of competitors and market growth rate; firm characteristics—firm age and ownership; product characteristics—products with digital characteristics and search vs. experience goods; macro environment–economic growth and equity market level. The inclusion of some of the variables is also based on the theoretical framework for success in online retailing proposed by Mahajan et al. (2002).

Given the dynamic nature of the online marketplace, it is appropriate to explore these determinants in the context of industry evolution. For this purpose, the current study employs a duration model. The incorporation of not only time-varying covariates, but also time-varying coefficients is a new methodological approach in marketing. There are several developments associated with the Internet channel that justify the selection of the above factors and the exploration of their dynamic nature. These are discussed in detail in the sections below.

Competitive strategy

Order of entry

Early marketing studies based on the theoretical-analytical economic framework of first-mover advantages find that market pioneers are rewarded by long term market share advantages (e.g Robinson & Fornell, 1985). First-movers gain advantages because of their ability to raise entry barriers due to scale effects, advertising, consumer switching costs, etc. The entry barriers allow pioneers to extend their "natural" monopoly period and thus be able to accrue profits that would later help them to compete.

Subsequent studies (Golder & Tellis, 1993; Lilien & Yoon, 1990) challenged these findings based on survival bias indicating that many true pioneers face the risk of failure. The controversy has continued in more recent studies: Robinson and Min (2002) show that pioneers in industrial markets have higher survival rates compared to second entrants; and Boulding and Christen (2003) conclude that the market share advantage of pioneering is often offset by the greater cost disadvantage. In the online retailing setting, Nikolaeva et al. (2006) find survival advantages for introductory stage entrants, but their study does not include mature stage entrants.

One factor that has been largely overlooked in this literature is the time effect (except for Lilien & Yoon, 1990). The underlying question is not whether first mover advantages exist, but how long they last. Collectively, all of the above studies seem to support the idea that a later entrant with a superior composite product backed by large advertising expenditures can overcome the pioneer. The longer we track industries, the more likely is the entry of a superior late mover (e.g. Golder & Tellis, 1993).

In other words, early entrants might be experiencing artificial advantages in the early period after their introduction, which can easily disappear once the industry reaches equilibrium. The following comparison helps to illustrate the above argument. Kalyanaram and Urban (1992) show that later entrants reach their asymptotic market share at a faster rate compared to early entrants. In a sense, this happens because early entrants have to "wait" for the late followers to enter, which eventually brings market shares to their asymptotes. Consequently, during the "waiting" period, early entrants have less competitors and as a result higher market share. Other factors that can contribute to early movers' advantages during the "waiting" period are technology cost and know-how, better financing, as well as consumers' unwillingness to switch to less known competitors. Therefore, early entrants may be less prone to early exit. However, with time and the entry of more competitors, market conditions become more adverse and the advantages enjoyed by early entrants under milder conditions disappear.

Since late followers enter under worse market conditions, they tend to exit more often early after their entry and the ones who survive are well equipped to successfully challenge their predecessors. This is observed in technologically intensive industries (Kerin, Varadarajan & Peterson, 1992). Although some followers may be at a disadvantage when they enter the industry, they may be better adapters and ultimately even perform better than pioneers. Thus, first mover advantages may be easier to observe in the early stages of a firm's entry into a new industry.

In line with the proposition of Kerin et al. (1992) about the nature of order of entry advantages in technologically intensive industries, it is worthwhile pointing at several characteristics of the online environment that suggest that early entrants' advantages may be short lived. First, the Internet lowers consumer switching costs (Bakos, 1997), which has been shown to shorten first mover advantages. In addition, the greater information richness (Varadarajan & Yadav, 2002) would make it easier for consumers to explore new, unfamiliar options, which can steer them away from early entrants. Accordingly, while consumers might have been hesitant to patronize Overstock.com in 2000 (the company launched its store at the end of 1999) in face of the uncertainty about the e-tailer's future, over time the e-tailer managed to attract enough customers to become one of the top 20 online retailers in 2004. Second, online retailing has short time periods between entries, which has been shown to shorten first mover advantages (Huff & Robinson, 1994). A third factor pointing in the same direction is the high market development costs. Since the Internet channel was a radical innovation (Debruyne & Reibstein, 2005), market development costs are usually high, which can benefit later entrants (Lilien & Yoon, 1990). These factors suggest that early mover advantages in online retailing may be limited and dissolve quickly.

Contributing to the diminishing advantage of early entry might be a second generation of entrants—firms that enter after a massive wave of exits and occupy market space vacated by the exitors. Agarwal et al. (2002) cite evidence from prior studies that the mature phase is characterized by a transformational change that drastically alters market conditions in the industry. During the mature phase, the industry infrastructure is well established, knowledge is widespread, and procedures are standardized. By and large, mature phase entry is at a lower rate and qualitatively different. In the case of e-commerce, the mature phase coincides with a period of low resource munificence (Park & Mezias, 2005). Therefore, late entrants are well prepared to resist turbulences, do not depend on exuberant financing, and come with lessons from the shakeout. In addition, uncertainty is highly reduced compared to the growth phase. This allows late entrants to find strategic niches and coexist with incumbents.

Based on the above arguments, two hypotheses are developed. The first one addresses the order of entry effect and its changing nature over time. The second one follows the theoretical lines of two distinctive industrial regimes cited by Agarwal et al. (2002). It argues that firms who enter after the massive wave of exit of an industry have an advantage.

H1: Order of entry is positively related to e-tailers' probability of exit, but the effect diminishes over time.

H2: Mature phase entrants have a lower probability of exit compared to earlier entrants.

Publicity

While publicity is an important part of the promotional mix, its effect on company performance is frequently ignored. Duncan and Moriarty (1998) show that message sources are quite influential in shaping consumers' beliefs about companies. On the Internet, Drèze and Zufryden (2004) find a positive relationship between publicity and web site traffic.

If increased publicity leads to increased web site traffic, then we can expect that higher traffic translates into higher sales. In general, publicity is a function of the company's PR efforts, size, and visibility. Companies that are bigger and spend more on advertising are more visible and more newsworthy hence they attract more media coverage. All these factors can enhance the survival chances of a firm. This allows for the following hypothesis:

H3: Publicity is negatively related to e-tailers' probability of exit.

Distribution channels

Mahajan et al. (2002) theorize that online retailers with existing offline experience would perform better than single-channel e-tailers because of their existing market-based assets that include branding and customer relationships. Accordingly, Nikolaeva et al. (2006) find that multi-channel retailers register fewer exits compared to pure online start-ups. Because the advantages of clicks-and-mortar retailers like brand equity transfer, improved customer relationships, and cross-channel synergies allow them to charge higher prices, their survival rates are expected to be consistently higher compared to single-channel e-tailers. Therefore, no dynamic hypothesis is developed.

Industry structure

Competitive density

In the strategy/organizational ecology literature, competitive density is the number of competitors in a product category in a given time period. If increasing density increases organizational exit rates, the environment is competitive. On the other hand, if increasing density increases survival rates, this indicates mutualism (Baum & Mezias, 1992). Some studies have found a U-shaped relationship between competitive density and failure risk accounting for legitimizing and competitive forces (Agarwal et al., 2002; Carroll & Hannan, 1989). However, citing a number of organizational studies, Aldrich (1999) points out that the U-shaped relationship is not applicable to all industries.

Perhaps the strongest argument for e-tailing being one of the industries where the U-shape theory does not hold is the high environmental munificence (the level of resources in an environment) marking the formative stages of the industry (Park & Mezias, 2005). Aspects of the high environmental munificence associated with online technology included aggressive investments, generous R&D grants, exuberant expenditures in marketing and technology, high demand for skilled, technologically-savvy labor, etc. (Park & Mezias, 2005). This is in contrast to the premise of the U-shape studies that at the initial stages, creditors, suppliers, employees, and customers are cautious to deal with newly established firms decreasing their survival chances (Aldrich, 1999). Therefore, the period of high munificence confutes the hostile environment characteristics of the early stage of industries where the U-shaped relationship between population density and exit is observed.

Because of the high environmental munificence, firms at low population levels did not face adverse market conditions affecting negatively their survival chances. Looking at introductory and growth stage entrants, Nikolaeva et al. (2006) do not find a *U* shaped relationship indicating legitimizing effects. In further support, the first web site shut down happened in the middle of 1999 and exits did not start picking up until one year later. Thus:

H4: Competitive density is positively related to e-tailers' probability of exit.

Market growth rate

While growing markets are characterized by increased sales that would imply lower exit risk, high-growth markets also attract many competitors. Agarwal and Bayus (2002) show that firm takeoff precedes sales takeoff in various industries. This means that markets with high sales growth rates are more competitive. Day, Fein, and Ruppersberger (2003) also observe that high growth markets attract followers who are "naïve about the barriers to entry and don't realize how many others are also poised to enter at the same time" (p.131). In addition, the positive correlation between entry and exit rates has been documented in the economics literature (Horvath, Schivardi & Woywode, 2001). In summary, even though the growth of a market increases the size of the pie, it has to be sliced into thinner slices, which leaves the question of the effect of market growth rate on survival open. This leads to two alternative hypotheses:

H5a: Market growth rate is negatively related to e-tailers' probability of exit.

H5b: Market growth rate is positively related to e-tailers' probability of exit.

Firm characteristics

E-tailer age

Firm age is a variable that has been heavily used in the strategy literature, but has been marginalized in marketing. Firm age reflects a company's experience. Subsequent events build on the routines and competences as well as the emotions characteristic of the founding period. They become the standard against which future events are evaluated (Aldrich, 1999).

Because many Internet retailers entered during the period of high environmental munificence, their initial endowments were substantial. That might have created a spirit of exuberance not easily matched by subsequent events. Prior research has observed that firms can grow rapidly and adaptively while the initial endowments last and when the endowments are exhausted, growth slows down or some firms may be forced to exit (Aldrich, 1999). This is the basic argument of the liability of adolescence theory (Henderson, 1999). Clearly, the situation in the Internet retailing population was similar—with the financial cushion of venture capital or backing from parent companies, exit rates in the formative years are low. As e-tailers burn through their initial capital, exit rates increase over time. Once equilibrium is achieved, exit rates eventually decline. This scenario is reflected in the following hypothesis:

H6: E-tailer age follows an inverted-U type of relationship with the probability of exit.

E-tailer ownership

Since the development of e-commerce was closely associated with the boom and burst of the equity markets, it is of interest to compare publicly traded companies and private ones. Maug (2001) states that publicly traded companies are better off when industry information is more important. They can use the information aggregated by the stock market and communicated back to the firm by the stock price. Eventually, this information helps the firm make more informed decisions. Since online retailing was a new industry, firms required plenty of outside information to judge its viability. This means that public firms were in a better position.

Another argument in favor of publicly traded companies is their resource base. If the market favors the new technology, as was the case with e-commerce, they can raise more capital to adopt the new technology. However, this would matter more in the early stages. Once the companies establish themselves, the difference in survival probabilities between public and private companies should disappear. When competition becomes more intense, firm-specific information would be as critical as market-specific information, thus leveling the playing field between public and private companies. Private companies that have survived the turbulent period should not be less viable than publicly traded companies. Thus:

H7: Publicly traded e-tailers have a lower probability of exit compared to privately owned e-tailers, but the effect diminishes over time.

Product characteristics

Products with digital characteristics

Mahajan et al. (2002) theorize that one of the success factors in e-tailing is selling digital vs. physical products. They define digital products as products that can be digitized and transmitted electronically like music, electronic books, software, and video. These products can be efficiently distributed online, because they are information rich and do not require physical space for storage. However, as recognized by Mahajan et al., the technology has not reached the level where these products are distributed exclusively in their digital form. Another reason for the predominantly physical form of the products is the fear of piracy.

As noted by Varadarajan and Yadav (2002), physical and digital product substitutes may co-exist. The majority of e-tailers who sell digital products derive most of their sales from the products in their physical form. Therefore, it is useful to look at the physical substitutes of digital products. We can refer to them as products with digital characteristics.

These products are standardized, touch and feel is not important; and they are easy and cheap to ship. Many e-commerce pioneers started selling products in these categories. The universality of the products, however, does not leave much room for differentiation. This implies that the advantages of e-tailers selling products with digital characteristics will dissipate with time. Furthermore, as customers become more comfortable with the online shopping environment, they will be spending more money on products for which touch and feel is important. E-tailers of such products who win customers' trust in their first years of operation should be on an equal footing with e-tailers of products with digital characteristics later on in their lives. This effect of time is incorporated in the next hypothesis:

H8: E-tailers of products with digital characteristics have a lower probability of exit compared to other e-tailers, but the effect diminishes over time.

Search goods

Mahajan et al. (2002) argue that search goods are more appropriate for the Internet. Search goods do not need to be examined before purchase, because they can be fully described, whereas experience goods have to be tried by consumers before they are fully evaluated. Since the Internet deprives consumers of the tactility characteristic of products, it becomes even more difficult for consumers to evaluate experience goods. Therefore it is expected that e-tailers selling search goods would perform better than e-tailers selling experience goods.

On the other hand, Varadarajan and Yadav (2002) propose that for products for which the tactile feedback is important, the opportunity to convey more information over the Internet is likely to benefit the sales of these products. This argument becomes stronger when customers accumulate sufficient experience with e-tailers. Therefore, the distinction between search and experience goods might disappear over time. In reality, most products fall on a continuum between search and experience characteristics. If search is on the lower end of the continuum and experience is on the higher, then:

H9: E-tailers' score on the search-experience continuum of products is positively related to their probability of exit, but the effect diminishes over time.

Macro environment

Economic growth

In times of general economic prosperity, firms should find survival easier. Golder and Tellis (2004) hypothesize that a change in the economic environment would cause a change in sales in the same direction. Increasing sales should lessen the probability of exit. In a similar line of thought, Baker and Kennedy (2002) document the negative relationship between GDP growth rate and firms' distress delisting rates from the major stock exchanges.

Economic growth is reflected by the equity markets. Since the NASDAQ index tracks many technology companies, it played a special role in the Internet economy. Furthermore, almost all of the e-commerce companies that issued public stock joined NASDAQ. The NASDAQ index can also be related to the availability of venture capital. High growth rates are associated with high demand expectations that make venture capitalists pour more money into new ventures. Therefore, in general, periods of high growth in the stock market are associated with greater financial stability, which should decrease failure probability. Thus:

H10: Economic growth is negatively related to e-tailers' probability of exit.

Equity market level

Equity market levels signal market expectations for future demand. Based on the above comments, NASDAQ was a particularly strong signal for e-tailers. High growth expectation markets usually attract many entrants. Day et al. (2003) point out that during the boom period "an unsustainable glut of competitors is attracted by forecasts of high growth and promises of exceptional returns" (p.131). Botman, van der Goot and van Giersbergen (2004) report several papers in the finance literature documenting that firms that go public during "windows of opportunity" characterized by high equity market levels underperform relative to other offerings. These "opportunity windows" usually result from over-optimism about the earnings potential of young growth companies. The authors find a positive relationship between market level at the time of offering (measured as the average value of the NASDAQ composite index during the month of offering) and a firm's hazard of exit (Botman et al., 2004).

The flip side of abundant venture capital is relaxed criteria resulting in riskier projects. Consequently, e-tailers who enter during periods of high growth expectations tend to be less prepared to survive the adjustment period in the industry. However, the ones who utilize their initial endowment wisely and develop adequate strategies and operations would later have higher survival chances. Accumulating experience with customers and moving along the learning curve can strengthen the strategic position for companies who entered at times of high growth expectations. This dynamic effect is expressed in the following hypothesis:

H11: A higher equity market level at the time of an e-tailer's entry tends to increase the probability of exit, but the effect diminishes over time.

Data

The sample of 460 online retailers includes all major web merchants within a category as well as smaller ones that received some media coverage. It is an extension of a dataset used by Nikolaeva et al. (2006) and a more detailed description is available from the author. The 17 categories appearing in Table 1 are based on the consumer shopping portal Bizrate. Since none of the e-tailers entered the market before 1994, the data span January 1994 through September 2003.

Based on information from the retailers' web sites, various media sources, Yahoo's finance site, and government statistics, the following data were collected: the month and year of entry and exit (where applicable) for each retailer, opening monthly values of the NASDAQ composite index, quarterly GDP growth rate and electronic and mail order sales, number of media mentions from Lexis-Nexis (these are the number of articles and press releases mentioning the company—used to measure the publicity variable in the model), company ownership status, channels, and product categories. A panel of 17 experts–marketing faculty members at research universities—were asked to assign a score from 1=search to 10=experience to the above mentioned product categories. The average of their scores was assigned to the search-experience variable. (A table with variable definitions, descriptive statistics, and correlations is available upon request from the author.)

The average age of survivors is 4.65 years. The average life of e-tailers that exited the industry was 2.28 years with the shortest duration lasting only 1 month. Table 1 lists the length of the growth stage for the different product categories.

Because 316 e-tailers were still in business at the end of the period, the data are right censored. A breakdown of survivors and exitors by product category appears in Table 1. Table 2 lists the Kaplan-Meyer 1, 2, 5, and 7-year survival rates by categorical variables as well as the total number of firms who have exited by the end of the

Table 1 Length of growth stage for product categories and category survivors and exits

Product category	Growth stage in years	Operating	Exits	Total
Apparel	6.75	43	2	45
Auto parts	3.42	5	0	5
Books	5.83	20	6	26
Department stores	7.34	25	8	33
Electronics	5.67	26	10	36
Food & drink	5.16	19	18	37
Gifts & flowers	4.92	17	9	26
Hardware	4.42	10	1	11
Health & beauty	4.42	44	27	71
Home & garden	3.92	16	9	25
Music	4.91	14	9	23
Office	0.59	4	0	4
Pets	0.50	2	2	4
Software	6.09	25	10	35
Sports	5.08	13	4	17
Toys	5.25	21	19	40
Video	4.84	12	10	22
Total		316	144	460

Table 2 Survival functions and total number of exitors and survivors by hypothesized dichotomies

	All	Multi-channel	Single-channel	Non-digital	Digital	Public	Private	Growth	Mature
1 year	92%	97%	83%	90%	98%	98%	85%	91%	94%
2 years	83%	94%	67%	80%	92%	94%	71%	80%	90%
5 years	67%	86%	44%	66%	72%	82%	53%	62%	85%
7 year	59%	84%	32%	60%	59%	69%	48%	53%	85%
Exitors	144	34	110	110	34	39	105	129	16
Survivors	316	240	76	241	75	197	119	192	123
Log-rank test for equality of survivor functions		chi2(3)=100.30 Pr>chi2=0.00		chi2(3)=1.23 Pr>chi2=0.27		chi2(1)=43.00 Pr>chi2=0.00		chi2(1)=18.13 Pr>chi2=0.00	

observation period and the ones who are still in business. Further, Table 3 lists the survival rates by order of entry. These descriptive statistics give us some preliminary insights in the hypothesized relationships. For example, survival rates decrease with order of entry, but late entrants' survival rates are almost the same as the survival rates of the whole sample. The dichotomized survival rates show better outcomes for multi-channel, digital products, public retailers and e-tailers that enter the industry during the mature phase.

Model specification and estimation

The time to exit the online market space is censored at the end of the observation period. This requires the use of a duration model since standard regression techniques would produce biased results. Because the data are organized into discrete groups, a discrete time hazard model is a better choice than a continuous time model (Allison, 1982). The complementary log-log (cloglog) regression is the discrete time alternative of the Cox proportional hazards regression, which is popular in the marketing literature (e.g. Golder & Tellis, 2004). The cloglog formulation is commonly used in the population ecology framework (Agarwal et al., 2002; Henderson, 1999). There are several advantages of using a cloglog regression. First, it is derived from an inherent continuous process, which means that the estimates are also estimates of the continuous duration model. This also means that the coefficient estimates are invariant to the specification of time intervals (Allison, 1982). Second, the discrete time specification avoids some of the estimation hurdles of a continuous time model like ties–multiple firms exiting in the same period of time. Third, the cloglog regression allows the easy incorporation of time-varying covariates. Fourth, it can easily incorporate flexible specifications of duration dependence. (The cloglog specification is available upon request from the author.)

The estimation of the cloglog model requires re-organizing the dataset by creating a separate observation for each e-tailer for each quarter. Therefore, the unit of analysis becomes firm-quarter rather than firm. For each firm-quarter, we observe the values of the covariates and whether the e-tailer has exited in this quarter. If the e-tailer is still in business, then the observation is censored. If, for example, a firm exits in the seventh quarter, then we have seven firm-quarter observations–for the first six, the dependent variable is 0 and for the seventh, it is 1.

Grouping the data into discrete intervals results in 7,346 firm-quarter observations. In this setting, e-tailer age is the time variable in the duration model—it is identical with the life span variable and we cannot separate the age and time effects (they are used interchangeably). The separation of age and time effects has been a complex issue in the organizational literature [for a detailed discussion see the chapter on organizations and social change (Aldrich, 1999)]. Generally, the age variable in the model serves as a proxy for the transformations experienced by firms. The age hypothesis introduced earlier predicts significant effects for a second degree polynomial in e-tailer age.

Table 3 Survival rates by order of entry

	All	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	>10
1 year	92%	100%	100%	100%	100%	100%	100%	91%	94%	100%	85%	89%
2 years	83%	93%	94%	100%	93%	93%	94%	91%	78%	100%	69%	79%
5 years	67%	85%	76%	82%	84%	80%	70%	82%	56%	77%	37%	67%
7 year	59%	44%	63%	68%	84%	72%	63%	82%	56%	na	na	na
Log-rank test for equality of survivor functions				chi2(10)=16.74 Pr>chi2 =0.08								

Further, McCall (1994) points out that the Cox proportional hazards regression requirement of constant coefficients over time often does not make sense from the point of view of the pertinent theory. Therefore the relevant covariates are interacted with the time variable–e-tailer age. To investigate any non-linearity in the time effect, the covariates were interacted with the second-degree polynomial of age. However, none of the second-degree polynomial interactions were significant; hence, they are not included in the model. Since the NASDAQ variable is correlated with the order of entry variable (r=0.78), the following two separate cloglog regression equations are estimated:

$$\begin{aligned}\log[-\log(1-h(t))] = {} & \alpha_0+\alpha_1 EA_{it}+\alpha_2 EA_{it}^2+\beta_1 OE_i+\beta_2 OE_i\times EA_{it}\\ & +\beta_3 SC_i+\beta_4 PB_i+\beta_5 CD_t+\beta_6 MG_t\\ & +\beta_7 P_i+\beta_8 P_i\times EA_{it}+\beta_9 D_i+\beta_{10} D_i\times EA_{it}\\ & +\beta_{11} S_i+\beta_{12} S_i\times EA_{it}+\beta_{13}\Delta N_t+\beta_{14}\Delta GDP_t\end{aligned} \quad (1)$$

$$\begin{aligned}\log[-\log(1-h(t))] = {} & \alpha_0+\alpha_1 EA_{it}+\alpha_2 EA_{it}^2+\beta_1 N_i+\beta_2 N_i\times EA_{it}\\ & +\beta_3 G_i+\beta_4 SC_i+\beta_5 PB_i+\beta_6 CD_t+\beta_7 MG_t\\ & +\beta_8 P_i+\beta_9 P_i\times EA_{it}+\beta_{10} D_i+\beta_{11} D_i\times EA_{it}\\ & +\beta_{12} S_i+\beta_{13} S_i\times EA_{it}+\beta_{14}\Delta N_t+\beta_{15}\Delta GDP_t\end{aligned} \quad (2)$$

where EA–e-tailer age, OE–order of entry, SC–single channel, PB–publicity, CD–competitive density, MG–market growth rate, P–public, D–digital products, S–search goods, N–NASDAQ, ΔN–NASDAQ growth rate, ΔGDP–GDP growth rate, G–growth phase entrant, h(t)–probability of exit, the subscript i stands for e-tailer and t for time period. Following the theoretical development in the hypotheses part, the modeling of e-tailer age is the specification of the baseline hazard. The left-hand side of the equation is known as the complementary log-log link (cloglog). The parameters are estimated by maximizing the likelihood function. A robust variance estimator was used to account for dependency of firm-quarter observations. For comparison purposes, the model was also estimated using Cox regression with robust standard errors. As another precaution, the model was estimated accounting for unobserved firm-specific factors assuming Gamma-distributed unobserved heterogeneity. Since the value of the Gamma variance is virtually 0 (0.000045), there are no signs of unobserved heterogeneity.

Results

Table 4 provides the results for the two models. Wald χ^2 is used instead of a likelihood ratio test because of the robust standard error estimations, but the interpretation is similar–a higher statistics indicates a better fitting model. Model fitting information accounting for the number of parameters is also given by the Akaike Information Criterion (AIC) as $-2\log\Lambda+2r$, where Λ is the likelihood and r is the number of parameters. All things being equal, the model with smaller AIC provides a better fit to the data.

Competitive strategy

The impact of order of entry expressed as time lag after the first entrant and its interaction with e-tailer age is estimated in Model 1. Since the dependent variable in the cloglog regression is the probability of exit, H1 predicts a positive sign for the order of entry coefficient, which is confirmed. The results indicate that each year delay in entry increases the chance of exit by 31% ([exp (0.27)−1]×100%). The negative sign for the interaction of order of entry and e-tailer age indicates that order of entry advantages diminish with time supporting the theory of dissipating pioneering advantages. Namely, the affect disappears after the first quarter of the third year.

The hypothesis (H2) that mature phase entrants are more viable than growth stage entrants, is tested in Model 2. The mature phase coefficient is negative and significant at the 10% level (p=0.053) indicating weak support for H2. As discussed, mature phase entrants face different entry conditions, which can help them occupy niches vacated during the preceding big exit wave. There is a cautionary note that part of the effect may be due to data censoring. However, we can see that even the 2-year survival rate for growth phase entrants is 80% vs. 90% for mature phase entrants. Nevertheless, the issue will benefit from further research.

E-tailers that receive more media coverage seem to survive longer. Thus, the predicted effect in H3 is confirmed by the statistically significant (p=0.014) negative coefficient of the publicity variable. While there are some studies showing that higher levels of publicity lead to higher web site traffic (e.g. Drèze & Zufryden, 2004), we need to be cautious about assigning a direct link between media coverage and survival rates. It is very likely that bigger e-tailers with bigger marketing expenditures are more frequently mentioned in the media. Therefore, it would be premature to conclude that media presence per se increases survival chance.

As observed previously (Nikolaeva et al., 2006), single channel e-tailers have more than four times higher exit risk compared to multi-channel e-tailers.

Industry structure

The effect of competitive density on the hazard rate is positive, which confirms hypothesis H4. Increasing com-

Table 4 Estimation Results—n=7346

Variables and Hypotheses	Model 1 Cloglog coefficient estimates (robust st. err.)		Model 1 Cox coefficient estimates (robust st. err.)		Model 2 Cloglog coefficient estimates (robust st. err.)		Model 2 Cox coefficient estimates (robust st. err.)	
Constant	−8.24	(0.76)***	–		−9.47	(0.76)***	–	
Order of entry (H1)	0.27	(0.14)**	0.25	(0.13)*	–		–	
Order of entry*E-tailer age (H1)	−0.12	(0.05)**	−0.11	(0.05)**	–		–	
Mature phase (H2)	–		–		−0.62	(0.32)*	−0.63	(0.32)**
Publicity (H3)	−0.001	(0.001)**	−0.002	(0.001)**	−0.002	(0.001)**	−0.002	(0.001)**
Single-channel	1.65	(0.24)***	1.65	(0.24)***	1.50	(0.25)***	1.50	(0.25)***
Competitive density (H4)	2.01	(0.68)***	2.10	(0.66)***	1.73	(0.66)***	1.79	(0.63)***
Market growth (H5)	1.71	(0.52)***	1.52	(0.48)***	1.71	(0.53)***	1.48	(0.49)***
E-tailer age (H6)	0.72	(0.32)**	–		1.12	(0.33)***	–	
E-tailer age^2 (H6)	−0.12	(0.04)***	–		−0.15	(0.04)***	–	
Public (H7)	−1.20	(0.38)***	−1.15	(0.38)***	−0.99	(0.40)**	−0.96	(0.39)**
Public*E-tailer age (H7)	0.39	(0.11)***	0.37	(0.11)***	0.35	(0.12)***	0.34	(0.12)***
Digital (H8)	−1.18	(0.36)***	−1.14	(0.35)***	−1.07	(0.38)***	−1.02	(0.37)***
Digital*E-tailer age (H8)	0.33	(0.12)***	0.30	(0.12)**	0.27	(0.12)**	0.24	(0.12)**
Search (H9)	0.11	(0.06)*	0.11	(0.06)*	0.10	(0.06)	0.10	(0.07)
GDP growth (H10)	−0.01	(0.002)***	−0.01	(0.002)***	−0.01	(0.002)***	−0.01	(0.002)***
NASDAQ growth (H10)	−1.69	(0.46)***	−1.56	(0.37)***	−1.61	(0.41)***	−1.39	(0.36)***
NASDAQ (H11)	–		–		0.73	(0.16)***	0.83	(0.17)***
NASDAQ*E-tailer age (H11)	–		–		−0.27	(0.09)***	−0.31	(0.10)***
LL	−564.87		−697.63		−559.88		−691.84	
Wald χ^2	288.53		263.46		342.36		300.75	
AIC	1161.74		1421.25		1153.76		1411.68	

*** Coefficients significant at 1%, **−5%, *−10%

petition makes resources scarcer and subsequently increases failure risk. In addition, increasing population density signals optimistic expectations, which attract poorly prepared or overly optimistic founders—a process that ultimately results in higher exit rates (Aldrich, 1999). Increasing online competition also forced e-tailers to spend a large percentage of their founding capital on inefficient marketing contributing to their demise.

The market growth covariate is positive and significant indicating an increasing hazard of exit with market growth–a support for H5b. This is probably due to the opposing forces accompanying the market growth rate–while the market is expanding, the competition is growing as well, which requires higher marketing expenses thus decreasing the survival chance of e-tailers. The preceding argument of a growing market attracting naïve entrepreneurs also explains the observed support for H5b.

Firm characteristics

The impact of e-tailer age on the hazard rate follows an inverted-U curve, which supports H6. This means that in the very beginning the hazard of exit is low and gradually grows over time until it picks at about 6 years and then it starts decreasing. This is not surprising in the online retailing context, because many entrants started with big initial endowments. As they deplete their initial endowments, exit chances increase. The ones who survive have had the opportunity to improve their strategies and to redeploy resources in a more efficient way. As they age, the market turbulence is decreasing as well and survival chances increase.

The results confirm H7–public e-tailers have more than 60% lower exit rates in the formative years, but after about 3 years, the effect disappears. It seems that the private companies, which manage to overcome the difficulties in the formative years and accumulate sufficient capital do not suffer from any disadvantages compared to public companies. They may be even more flexible once proprietary firm knowledge becomes more crucial for success.

Product characteristics

As stated in H8, e-tailers in categories of products with digital characteristics tend to have close to 70% lower exit rates in the formative stages. This result is not surprising, because books, music, video, and software were the first products to be sold online. However, as customers become more comfortable with the Internet channel, the distinction disappears in the second half of the third e-tailers' year. This is confirmed by the latest numbers about online sales–according to data released by ComScore Networks, the fastest growing category of online sales in 2005 was apparel and accessories, which increased by 36% (press release from 1/5/2006—http://www.comscore.com/press/pr.asp). This result is another confirmation of the fast changing nature of survival determinants.

Turning to search goods, it is important to differentiate them from products with digital characteristics. For example, books and movies have to be consumed before full evaluation is possible. The results indicate a marginal support for the search goods hypothesis–H9. The variable scale increases from search to experience. Thus, a positive sign of the coefficient means that e-tailers who sell products on the higher end (experience) of the continuum face higher exit rates. The coefficient is significant at the 10% level ($p=0.079$) only in Model 1. The interaction with age was not supported indicating that the rising popularity of experience goods on the Internet does not seem to be adversely affecting sales of search goods.

Macro environment

In order to test H10 predicting a positive relationship between economic growth and survivorship, the model incorporates two variables—the GDP growth rate and the NASDAQ composite index growth rate. In support of H10, both coefficients are negative and highly significant in both models. A better economic milieu and increasing availability of venture capital contribute to lower exit hazards. Since economic growth is tightly related to the level of resources in a particular environment, the results confirm prior findings of the relationship between environmental munificence and firm survival (Park & Mezias, 2005).

Looking at the equity market level represented by the NASDAQ values at the time of e-tailer entry, the coefficient estimate in Model 2 is positive and highly significant, which supports the relationship proposed by H11. This means that e-tailers entering during high equity market levels have higher risk of exit. To quantify the result, e-tailers entering during NASDAQ levels of 3,000s faced 108% higher failure risk compared to firms entering during NASDAQ levels of 2,000s. The explanation is in line with the observation of Day et al. (2003) that high demand expectations lured many e-tailers that did not have sustainable business plans to enter the market. Also, as suggested in the theoretical development, the effect is not constant over time—the coefficient of the interaction of NASDAQ and e-tailer age is negative and significant. It appears that e-tailers who managed to survive the turbulent years were able to narrow the disadvantage gap. For the e-tailers who entered with solid strategies responding to high demand expectations, the effect dissipates after the third quarter of the second year.

Summary and conclusions

The current study empirically tests Varadarajan and Yadav's (2002) theoretical framework of marketing strategy in the Internet context. It investigates how elements of competitive strategy, industry, firm, and product characteristics, as well as the macro environment affect survival of online retailers. The unique feature of the inquiry is that it examines the survival determinants' time-varying nature. To the best of my knowledge, it is the first study in the marketing literature to explore time-varying coefficients in a duration modeling context.

The focal point of the competitive strategy variables is the order of entry effect. The results are intriguing, because they come as a reconciliation of the debate in prior studies on the existence of first mover advantages. Since early entrants have fewer competitors, they are able to enjoy some initial advantages. As time progresses and more competitors enter the market, the pioneering advantages dissipate. In addition, the results suggest that mature stage entrants may be more viable compared to growth stage entrants due to the transformational change occurring in the industry and the vacated market niches after the wave of exits. Managerially, the results demonstrate the fallacy of an early entry strategy as a source of sustainable competitive advantage. Early entrants like CDNow, E-toys.com, and Garden.com who enjoyed early category leadership are examples of this fallacy.

Investigating the relationship between publicity and survival is another way to proxy for a resource related strategy variable in the absence of better data. The estimated negative coefficient confirms the hypothesis prediction that e-tailers with more media presence have lower exit risk. While publicity by itself can increase web site traffic and consumer trust thus leading to higher longevity, such a conclusion would be hasty in the absence of more data. Nevertheless, e-tailers can only benefit from strategically tailored publicity campaigns. Further, as shown in prior studies, single-channel retailers can look for alliances with traditional retailers in their product category. For example, Amazon's alliance with Toys'R'Us allowed it to outpace the early category leader E-toys.com.

Looking at industry structure, the results reveal that exit rates increase with increases in competitive density. According to Baum and Mezias (1992), this is indicative of a competitive environment. The growth of the market both in terms of firms and sales increases the hazard of exit, which can be explained by intensified competition, lower margins, and higher marketing expenses. It appears that the high growth market attracted many naïve entrants who were not able to compete successfully in a crowded marketplace. This is to show that entry strategies should be evaluated carefully and even more so during periods of high market growth. Overoptimistic prognoses based on a rapidly expanding market can be disastrous to a firm.

Age effects are interpreted as accumulation of organizational knowledge. The inverted-*U* type relationship of exit hazard with e-tailer age is reminiscent of the liability of adolescence theory. The implication is that e-tailers should make wise use of their initial capital and accumulate market experience and knowledge that will be useful after the initial honeymoon period. Publicly traded companies seemed to be more successful during their early developmental stage, because they are in a better position to accumulate and interpret environmental knowledge. Judging by the dissipation of the advantage with time, it seems that internal company knowledge and experience become more important as companies age.

Turning to product characteristics, it appears that the advantages of e-tailers selling products with digital characteristics were not long lived either. In the beginning, e-tailers selling books, music, video, and software registered higher survival rates. In fact, this advantage is the longest lasting among the variables with time-varying coefficients tested in the model. However, as customers' acceptance of the online channel increased, these e-tailers found it more difficult to establish their own niches–many of them were forced to succumb to the power of Amazon.com. The distinction was not so obvious when comparing search and experience products. There is some evidence to suggest that e-tailers selling products with more search characteristics fare better, but it is not evident across the two models. These results demonstrate that there are no products that have a stronghold in the online channel.

Finally, the effect of macro environmental factors on firm performance should not be underestimated. As expected, economic growth is beneficial to e-tailers. While the GDP is a proxy of the general economic environment, the NASDAQ index growth might be indicative of market expectations and capital availability. High environmental munificence increases e-tailer survival chances. Another important finding is the positive relationship between the equity market level at the time of entry and e-tailers' exit hazard. It is in confirmation of prior findings that high demand expectations attract premature and weaker entry (Aaker & Day, 1986; Day et al., 2003). Since the most unprepared entrants exit fast, the survival differences decrease over time. Managers who are prepared to meet the ordeals of high-growth markets can expect brighter future at the onset of maturity.

As any empirical study, the current one has its limitations. One of them is the lack of some important variables that are not in the public domain. The study would have greatly benefited if company information on size and marketing expenditures were available. The analysis would have been more meaningful within strata of companies of different sizes. Further, there were speculations in the industry press that the main reason for the failure of many e-tailers was their unreasonably high marketing budgets. Data availability would have allowed the test of this hypothesis as well as the separation of the publicity effect. Another limitation of the publicity variable is that it lacks any qualitative information, i.e. we do not know whether the articles mentioning an e-tailer are on the positive or negative side. Other data of interest are the type and number of alliances. As Varadarajan and Yadav (2002) point out, one of the new realities of integrating the online channel in the company's strategy is the opportunity of online networks of alliances.

Another potential limitation of the study is the interpretation of the stock market effect. While it is true that in more general terms the stock market reflects the general situation of the economy and expectations of market growth, it is a much broader compilation of various factors. This study offers one possible explanation of the NASDAQ effect. It is an interesting effect and future research can certainly delve more into it and offer other explanations.

Conclusion

Studying the evolution of online retailing illuminates important aspects of marketing strategy in the Internet framework. Most importantly, this research demonstrates that as an industry evolves so do strategic variables. Therefore, marketing strategy should be examined in its dynamic context. From a managerial standpoint, it is important to understand that some factors offering strategic advantages in the formative stages can dissipate over time. In the case of online retailing this happens fairly quickly–between 2 and 4 years after entry. Consequently, companies should make the adequate steps in overhauling the change in strategic positions.

Investigating the dynamic nature of survival determinants allows us to see that there are very few factors whose effect does not change with time. For the Internet retailing industry characterized by great transparency, this carries the fundamental implication that companies should constantly reinvent their strategies and operations in search of sustainable competitive advantages. This is reflected in a recent industry article where e-tailers are advised to make formal strategic plans and review them every quarter (Gardner, 2007). For the research community, the study demonstrates that time effects are important in a dynamic industry and they should not be ignored in future studies.

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