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Pricing e-service quality risk in financial services

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ABSTRACT

E-service quality is crucial for differentiating e-commerce offers and gaining competitive advantage. *E-service quality risk* is the risk that a firm's e-service quality will drop, or improve, relative to competitors. There is evidence that benchmark ratings of e-service quality that are published regularly by third-parties can impact the market value of rated firms. Firms therefore continue investing in IT-related determinants of e-service quality. However, they do so without knowing: (1) the cost or return associated with a unit relative deterioration, or improvement in e-service quality ratings, and (2) how this cost or return may vary across firms. To answer these questions, we adapt a well-established financial risk pricing approach for the case of pricing a single idiosyncratic IT investment risk, where an event study is used to generate the market data needed to price risk (Thompson 1985). We then apply the approach with Keynote's biannual e-service quality ratings for firms in six financial services sectors. We find that firms' sensitivity to e-service quality risk depends primarily on the sector to which they belong, and also on their size and growth potential. Our results suggest a cap on the amount that different firms ought to spend to achieve a unit improvement in relative e-service quality ratings. The risk pricing approach presented can be applied for other important IT investment risks, and the risk pricing information it yields may open up new ways to approach fundamental IT investment problems.

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1. Introduction

Announcements of e-service launch initiatives have been seen to benefit the market value of the launching firms (Subramani and Walden 2001, Geyskens et al. 2002, Cheng et al. 2007, Lin et al. 2007). *E-services* involve the use of information technologies (IT) via the Internet to enable, improve, enhance, transform or invent a business process or system to complete tasks, solve problems, conduct transactions or create value for current or potential customers (Sawhney and Zabin 2001, Wu et al. 2003). Using e-services, firms can provide rapid customer response, improve service quality, enhance operational efficiency, and reduce costs.

E-service quality is a crucial determinant in differentiating e-service offers and building a competitive advantage (Santos 2003, Rust and Miu 2006). *E-service quality* is determined by IT-related factors, such as website security and functionality, and by product and process factors, such as product variety and order delivery timeliness (Collier and Bienstock 2006, Rowley 2006). Superior e-service quality can improve customer satisfaction, customer acquisition, and customer retention (Boulding et al. 1993, Ranaweera and Neely 2003, Lee and Lin 2005).

With the payoff from e-service quality, however, also comes risk. E-service quality risk is the risk that the e-service quality of a firm will change - deteriorate or improve - relative to that of competitors. This definition recognizes that risk can be negative or positive, consistent with the way much finance research defines risk as the possibility that things will deviate from expectations (Elton and Gruber 1995).¹ Companies can develop their own measures of e-service quality, but many rely on third-party benchmark measures such as those from Keynote, Bizrate, and ePublicEye. Keynote (www.keynote.com), for example, uses its GomezPro Scorecard (GPSC) to rate companies' e-service quality based on how customers assess those companies' websites along IT-related determinants, including: functionality, content availability, accuracy of online transactions, ease of use, and security (Al-Hawari and Ward 2006). Keynote's benchmark ratings are published regularly for the top 20-30 companies in each of numerous business sectors (e.g., banking,

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¹ This definition contrasts with the way much of the research on IT has defined risk as a negative loss event having a probability of occurrence and a loss amount. Instead, it follows a growing body of IT research that has been using the latter view, for example, in the context of real options analysis (Benaroch and Kauffman 1999, Benaroch and Appari 2010).

insurance, brokerage). Firms whose benchmark e-service quality ratings showed superiority over competitors have used them to boost their strategic position (e.g., Citigroup Inc 2004), and as a result, firms whose ratings show inferiority feel pressured to invest in improving their e-service quality (Carpenter 2005, Wright and Dawson 2004). Unless specified otherwise, for brevity we will hereafter use the term *benchmark e-service quality ratings* to refer to competitive benchmark e-service quality ratings by a third-party.

The reality, however, is that most firms invest in controlling e-service quality risk without knowing what level of investment is "right" for each of them. That is, firms do not know the answers to fundamental questions: What is a suitable approach for pricing e-service quality risk? Can the approach inform the firms about the economic cost, or return, associated with a relative deterioration, or improvement, in the third-party benchmark ratings of their e-service quality? And, is the answer to the last question different for different companies, depending on their characteristics (e.g., size, growth potential, industry)?

This research seeks to answer these questions by presenting a finance-based approach for pricing risk and applying it to the case of e-service quality risk. Finance research prices risk in terms of two parameters: the sensitivity of an asset to a particular risk, and the risk premium measuring the extra return that the stock investor community expects to earn on the asset per unit exposure to that risk (Elton and Gruber 1995). By telling us the value that stock investors associate with a unit change in exposure to a particular risk, these risk pricing parameters could suggest a limit on the amount that a firm ought to spend to achieve that level of improvement in exposure to that risk. The financial risk pricing approach used to estimate these parameters works as follows. It starts with a linear multi-factor model linking the expected excess return on assets to the behavior of multiple systematic (firmindependent) risk factors,² and then uses arbitrage pricing theory to estimate the risk pricing parameters based on market data (Elton and Gruber 1995).

We will adapt this risk pricing approach for our needs because it makes some assumptions that may not apply in our context. The adapted approach starts with a single-factor model that is conditional on events reflecting the effect of a single idiosyncratic (firm-specific) IT investment risk factor. Thompson (1985) shows that such a conditional single-factor model captures the essence of the event-study methodology, which isolates abnormal stock returns reflecting the impact of unanticipated idiosyncratic economic events on the market value of firms experiencing those events. Here, the events of concern are the periodic publication of third-party benchmark ratings of e-service quality that show changes in firms' relative standing. We use five years worth of data of Keynote's bi-annually published GomezPro e-service quality ratings for firms in six financial services sectors (banking, mortgages, insurance, etc.). There is evidence that Keynote's benchmark ratings change the perception of stock market investors about firms' relative e-service quality and, in turn, about the firms' market value (Chen and Hitt 2002, Kotha et al. 2004). The adapted approach then uses arbitrage pricing theory to estimate the risk pricing parameters based on abnormal returns that firms experience as a result of changes in their relative e-service quality.

This article makes a contribution to IT and marketing research on e-service quality and firm value. It is the first to present an approach for measuring and pricing the risk associated with e-service quality. This approach goes well beyond extant research that only

links individual aspects of e-service quality to firms' financial performance (Barua et al. 2004, Anderson et al. 2004, Kotha et al. 2004, Chen and Hitt 2002). Risk pricing information opens new ways to think about the economics of a firm's e-service quality falling behind, or moving ahead, of the competition. In particular, it could help firms determine how much they should be willing to invest in improving their relative benchmark e-service quality ratings. Our results indicate that firms in only certain financial services sectors have a significant level of exposure to e-service quality risk as measured by third-party benchmark ratings, and that level appears to vary across sectors. Further, our results suggest that firm size and growth potential also influence how investors react to relative changes in firms' e-service quality risk, albeit their influence is notably lesser in magnitude. The latter means that firms within a particular sector have only slightly different sensitivities to e-service quality risk as measured by benchmark ratings, due to their firm-specific characteristics.

This article makes a broader contribution to the literature on IT investment and risk management. We believe that it is the first to adapt and apply a well-established financial risk pricing approach to idiosyncratic IT investment risk. Another adaptation of the approach has been presented and applied elsewhere for the case of software development risks, a somewhat narrower application (Benaroch and Appari 2010). The approach presented here permits the pricing of a range of IT investment risks that are of prime concern to organizations, including security risks, customer adoption risks, and technology maturity risks. The significance of this contribution is also in supporting the solution of fundamental IT investment problems, including the management of IT investment risk and of IT investment portfolios.

The remainder of the article proceeds as follows. Section 2 reviews literature on e-service quality and its relation to IT investment and financial performance. Section 3 presents our adapted risk pricing approach. Section 4 empirically applies the approach in the financial services context. Section 5 concludes with a discussion of the empirical results and the reasons behind them. It also discusses the implications of our results for research and practice, and the limitations of our work along with directions for future research.

2. Literature review

This section discusses the importance of e-service quality in ecommerce, reviews research linking e-service quality to firm performance, and outlines the role that third-party benchmark ratings of e-service quality can play in measuring the risk and return on investments in e-service quality. Fig. 1 depicts the relationships between key concepts underlying the next discussion.

2.1. E-commerce and e-service quality

IT and the Internet have expanded horizons for businesses, largely through the automation of service in e-commerce. A typical example is banking and financial services. According to the Association for Payment Clearing Services, the United Kingdom payment association, online banking there increased by 174% from 6.2 million customers in 2001 to 17.0 million in 2006, and, more broadly, the number of adults shopping online increased by 158% in the same period.

The basis for competition in e-commerce has shifted towards differentiation based on e-service quality (Rust and Miu 2006). Early e-commerce businesses were focused on reducing service costs and increasing efficiency. However, most companies realized quickly that selling commodities online at low prices resulted in low profit margins. This has given rise to a paradigm of e-service

² Finance research distinguishes *systematic (macro-economic)* risks that are pervasive in the economy and affect all assets from *idiosyncratic (firm-specific)* risks that are unique to individual firms. Investors can diversify their investments to reduced idiosynchratic risks (Elton and Gruber 1995).



Fig. 1. E-service quality in context.

that goes beyond simple automation of services towards differentiation via the quality of services offered. E-service quality and service quality in general are recognized to be a crucial determinant in differentiating service offers and building competitive advantage (Santos 2003, Bauer et al. 2005).

One stream of e-service research is concentrated on customer adoption issues (Wu et al. 2003). The bulk of this stream has looked at the determinants of e-service quality and their measurement. Many researchers consider e-service quality to be determined primarily by IT-related factors, including website ease of use, design, security and privacy, functionality, and information accuracy (Devaraj et al. 2002, Al-Hawari and Ward 2006, Yoo and Donthu 2001, Zeithaml et al. 2002, Rowley 2006). Some add product and process-related factors, such as product variety and order condition and accuracy on delivery (Collier and Bienstock 2006, Lee and Lin 2005, Rowley 2006). Another part of this research stream has examined how e-service quality relates to higher level business-type measures such as the customer web experience and behavior (Parasuraman et al. 2005, Wolfinbarger and Gilly 2003), customer satisfaction (Bai et al. 2008), intention to buy (Bai et al. 2008), switching costs and customer retention (Chen and Hitt 2002), and customer loyalty (Al-Hawari and Ward 2006).

2.2. Investments in e-service quality and firm performance

Another stream of e-service research has also linked the above measures of e-service quality with firms' financial performance. It seeks to confirm an obvious relationship that has been argued to exist among service quality, costs and financial performance (Zeithaml et al. 1996, Ranaweera and Neely 2003). Improved service quality ensures long-term gains in profitability by increasing the level of customer business (Reichheld and Kenny 1990) and the ability of a firm to attract new customers and convert current customers into repeat customers (Edvardsson et al. 2000). In the banking context, for example, e-service quality was found to directly and positively affect bank financial performance (Santos 2003, Al-Hawari and Ward 2006). Observed impacts of improved e-service quality in banking include the ability to attract more profitable, loval and committed consumers compared with traditional banking consumers (Fox 2005) as well as the ability to cut costs sharply (Zhu and Chen 2002). Both impacts suggest that the quality of e-banking services contributes to improved firm profitability (Moutinho and Smith 2000).

With payoffs, however, also come pressures to keep investing in improved e-service quality. For example, if banking e-service quality were to become standardized and undifferentiated among all competitors, it will be easy for customers to compare and switch from one bank to another (Evans and Wurster 1997). Companies need to continuously work at maintaining and enhancing their e-service quality relative to their competitors though, since this will discourage their customers from switching to competitors (Anderson and Srinivasan 2003). Moreover, in some sectors this need is further driven by pressure to offer customers emerging IT-based e-service options such as those facilitated by mass social media and Web 2.0 tools (Brechbühl 2007). As customer expectations continue to rise, no company can rest on its laurels for long in offering the highest perceived value to customers. In sum, failure to keep up in this "race" for improved e-service quality could expose a company to the risk of falling behind in its financial performance.

In this light, firms are becoming sensitive to the economics of e-service quality. Some observers argue that firms are eager to gauge the value created through e-service quality initiatives (Geyskens et al. 2002). Others argue that the offering of high and standard e-service quality should be managed to enhance overall financial performance (Al-Hawari 2006), relative to the risk and return associated with investment (or lack thereof) in e-service quality. This would enable firms to know how an improvement or deterioration in their relative e-service quality impacts their market value, and, whether the impact is equal for all firms in all sectors.

2.3. Third-party e-service quality ratings and firm performance

Some efforts have been made to answer such questions by examining the impacts of regularly-published benchmark ratings of firms' e-service quality by a third-party. Examples of such ratings are Keynote's GomezPro Scorecard, Bizrate, ePublicEye, and the American Customer Satisfaction Index (ASCI) on e-commerce. Keynote's GomezPro ratings, for instance, measure e-service quality based on IT- and website-related determinants, including: the availability of information (content), accuracy of online transactions, ease of use, provision of updated (timely) information, attractiveness (aesthetics), and security (Al-Hawari and Ward 2006). Competitive benchmark ratings provide better-rated firms with opportunities to capitalize on their prior investments in e-service quality. Companies such as Citigroup and Huntington Bank, for example, often issue press releases when their e-service quality ratings are favorable (Citigroup Inc 2004, Huntington 2007).³ At the same time, lower-rated firms have reason to feel pressured to increase their investment in improved e-service quality (Carpenter 2005, Wright and Dawson 2004).

In essence, regularly-published competitive benchmark ratings change firms' relative e-service quality standing, upward or downward, and produce negative and positive economic events that may result in abnormal stock market return around the ratings' publication dates. This reality is apparent from numerous studies linking third-party ratings of various determinants of e-service quality to firms' financial performance. Specifically, it was found that, when certain benchmark ratings of e-service quality show upward or downward changes from one period to the next in the relative standing of individual publicly-traded firms, the market value of those firms tends to change accordingly upward or downward (Chen and Hitt 2002). For example, a strong correlation between customers' online buying experience, as proxied by Keynote's GomezPro ratings, and the firm's long-term performance, as measured by Tobin's q, have been shown for a cross-section of retail industries (Kotha et al. 2004). Likewise, a 1% change in customer satisfaction, as measured by the American Customer Satisfaction Index (ACSI) for e-commerce,⁴ was shown to be correlated with a 1.016% change in shareholder value, as measured by Tobin's q, based on an examination of forty United States firms (Anderson et al. 2004).

In sum, this literature indicates that third-party benchmark e-service quality ratings can help to measure, or gain insight into, the return on investments in e-service quality. The rest of this article builds on this realization by presenting a model for pricing e-service quality risk as well as applying this model with data about third-party benchmark ratings of e-service quality.

3. Risk pricing model

This section presents the financial risk pricing approach along with its adaptation to the e-service quality context.

3.1. Multi-factor model

The financial risk pricing approach has been developed within the framework of a linear multi-factor return-generating process (Elton and Gruber 1995). This framework offers a systematic way of describing how expected returns of assets (e.g., stocks, projects) vary with the movement of their associated risk factors. Where a *risk variable j* is an uncertain observable characteristic of an asset or its contextual environment (e.g., inflation, technology maturity), a *risk factor j* is defined as the deviation of the *ex post* value of risk variable *j* from its *ex ante* expected value. For example, if the customer adoption rate for a particular service is a risk variable that is expected to be 20% but turns out to be 18%, the customer adoption risk factor equals -2%. This conceptualization of a risk factor as the deviation of an uncertain variable from its expectation is the norm in financial research (Elton and Gruber 1995, Cochrane 2005).

Assuming *J* risk factors, the finance literature commonly starts with the next *return-generating process* (RGP) specification as a way to explain the prices of traded assets:

$$\tilde{r}_i - \bar{r}_i = \beta_{i,1} \tilde{f}_{i,1} + \dots + \beta_{i,J} \tilde{f}_{i,J} + \varepsilon_i \quad (i = 1, \dots, n, j = 1, \dots, J)$$
(1)

where $\tilde{f}_{i,j}$ is a stochastic mean-zero *risk factor*; $\beta_{i,j}$ is a *factor sensitivity* indicator measuring the degree of exposure of asset *i* to risk factor *j*; \tilde{r}_i is the stochastic risk-adjusted *return* on asset *i*; \bar{r}_i is the return expected if all factor sensitivities are zero; and ε_i is residual risk having an expected value of zero. A central assumption of the finance literature on pricing risk from the perspective of market investors is that only *systematic (macro-economic) risk factors* matter and command a premium return.⁵ As a result, this literature relies on a version of the RGB specification in Eq. (1) which requires that all assets should experience identical factor realization values, that is, $f_{i,j} = f_{k,j} \forall i, k (i, k = 1, ..., n)$.⁶ We, however, rely on the original specification of Eq. (1) because our interest is in pricing idiosyncratic risk.

Because risk factors in the RGP specification in Eq. (1) do not necessarily represent monetary values, risk pricing relies on another relationship that is derived based on arbitrage pricing theory:

$$\bar{r}_i = \lambda_0 + \lambda_1 \beta_{i,1} + \dots + \lambda_J \beta_{i,J} \tag{2}$$

where λ_j is a *factor risk premium* indicating how much extra return is expected per unit exposure to risk factor *j*; and λ_0 is the return expected if all factor sensitivities are zero. Arbitrage pricing theory rests on the concept of "no arbitrage opportunities" and the *law of one price*.⁷ An arbitrage opportunity arises when investors can earn riskless profits without making a net investment. The law of one price states that, if two assets are equivalent in all economically-relevant aspects, they should have the same market price. Arbitrageurs enforce this law: if they observe a violation of the law, they will engage in arbitrage activity and in the process eliminate the arbitrage opportunity. In an arbitrage-free economy, arbitrage pricing theory can be used to price assets relative to one another based on their co-movement with risk factors.

3.2. Single-factor adaptation for an idiosyncratic risk

Most investments in e-service quality (and elsewhere) are nontraded assets and are exposed mostly to idiosyncratic risk factors. It is therefore necessary to adapt the financial risk pricing approach

³ A March 22, 2004 press release from Citigroup offers an excellent example [underline added]: The Citi Cards website ... has again scored the #1 position in the Q1 2004 Credit Card Scorecard published by Watchfire GomezPro, the benchmarking and website assessment services business unit of Watchfire Corporation. This is the fifth consecutive period the Citi Cards website has achieved the top spot. Watchfire GomezPro ranks the top Internet credit card sites bi-annually. Citi Cards also received the highest score in the Customer Confidence and Relationship Services categories. "The #1 Watchfire GomezPro ranking in the Credit Card Scorecard is another manifestation of Citi's leadership role in financial services and on the Internet." said Amy Radin, EVP of Citi Cards e-Business.

⁴ The American Customer Satisfaction Index (ACSI) (2009) for e-commerce (www.theacsi.org), for example, reported in March 2009 that the online financial services industry has plummeted 6.3–74% on the ACSI's 100-point scale, and that the individually-measured online brokerage firms also dropped in customer satisfaction. TD Ameritrade suffered the biggest drop, diving 11–71%. Fidelity and Charles Schwab, with scores of 80 and 78, maintained leadership positions even while suffering 5% drops in satisfaction. E*Trade dropped 6–69%, for a last place index position.

⁵ The exclusion of idiosyncratic risks does not mean that these risks have no economic significance. Rather, when financial assets are priced from the perspective of investors, the argument is that idiosyncratic risks need not be considered because investors can diversify them away. In particular, it actually is less costly for investors to diversify idiosyncratic risks than for publicly-traded firms owning the risk. For example, investors could do so by building an equally-weighted portfolio of twenty to fifty tradable assets (Malkiel 1999, Tang 2004).

⁶ This RGP specification imposes other requirements, but these have no relevance to the single-factor adaptation we present. These requirements are: (1) the factors are independent of one another and of the residual term; and (2) the residual terms ε_i across assets is independent, to accounts for all systematic risk factors affecting assets.

⁷ Arbitrage pricing theory rests on several other standard assumptions, which enable the use of market data for the estimation of risk parameters that are universal to all investors (Dybvig and Ross 1985). These include the following. (1) Agents are risk averse with a bounded utility function. (2) There is a risk-free rate for lending and borrowing money (in which case it must be that $\lambda_0 = r_f$). (3) There is no market friction – no transaction costs, no taxes or no restrictions on trading). And (4) agents hold homogenous expectations about the risk-adjusted return r_i that risky assets pay (i.e., they agree on the identity and number of factors important systematically in pricing assets).

to our context and specifically to the case of a single idiosyncratic risk factor.

Suppose a single risk factor causes some firm-specific (risk) events known to be associated with changes in the market value of the firms experiencing those events. These market value changes can be isolated using *event study analysis*. This analysis empirically quantifies the economic value impact of an event by examining abnormal stock price movements around the event date (Campbell et al. 1997, Binder 1998). It typically does so based on a market model, such as the capital asset pricing model, which implies the following RGP specification (Cochrane 2005):

$$\tilde{r}_i = r_f + \beta_i (\bar{r}_m - r_f) + \tilde{u}_i \tag{3}$$

Here \tilde{r}_i is the stochastic risk-adjusted return on asset *i*; r_f is the risk-free rate of return; \bar{r}_m is the expected return on the market index; β_i is the *sensitivity* of returns on asset *i* to the market returns; and \tilde{u}_i is a mean zero, independent disturbance term for asset *i*. The term β_i is also called the *amount of risk*, and the term $(\bar{r}_m - r_f)$ is called the 'price of risk'. Based on the capital asset model, the expected return on asset *i* is:

$$\bar{r}_i = r_f + \beta_i (\bar{r}_m - r_f) \tag{4}$$

Thompson (1985) shows that, conditional on the announcement of an unanticipated economic event, the expectation of the disturbance term \tilde{u}_i in Eq. (3) can be defined as the *abnormal return* effect of the event announcement. So, where $\tilde{u}_i = \tilde{r}_i - \bar{r}_i$, if the event responsible for the abnormal return effect is associated with a particular firm-specific risk factor, \tilde{f} , we can write Eq. (1) as a singlefactor RGP specification that is conditional on the occurrence of this event:

$$\tilde{u}_i = \beta f_i + \varepsilon_i \tag{1}$$

This single-factor model follows Thompson's (1985) logic that suggests a conditional RGP specification can account for the effects of specific idiosyncratic risk events. Thompson (1985) further shows that the conditional RGP captures the essence of the event-study problem, which is about estimating the parameters in the model and testing hypotheses about their magnitudes and significance levels. Hence, following the financial approach, the risk factor in RGP specification Eq. (1') can be priced using a standard application of arbitrage pricing theory according to the single-factor relationship:

$$\bar{r}_i = r_f + \lambda\beta \tag{2}$$

4. Model application to e-service quality

We now apply the adapted approach specified in Eqs. (1') and (2') to the pricing of e-service quality risk in the context of publicly-traded financial services firms. We describe the data, the analysis approach used to estimate the respective risk parameters, and the estimation results.

4.1. Data

For this study, what constitutes a risk event is not the mere publication of a competitive benchmark rating for firm *i* at time *t*, denoted $R_{i,t}$, but rather the *unanticipated relative change* in the ratings from publication time t - 1, defined as $\Delta R_{i,t} = [R_{i,t} - R_{i,t-1}]/R_{i,t-1}$. An underlying assumption of this definition is that rated firms invest at the same rate at their e-service quality, and therefore their relative e-service quality ratings are not expected to change. The premise is that when some firms deviate from this behavioral investment pattern and unanticipated changes in relative ratings do occur, they convey to investors important (positive or negative) risk information about e-service quality. If this information leads to noticeable stock price movements, those movements could be isolated using an event study and used thereafter to price e-service quality risk. It is important to add the possibility that stock price movements may actually be in response to relative changes in firms' order-rankings rather than in firms' scaledratings. We have included this possibility in the coming analysis, but we do not report the results because we found no statistical evidence to that being the case.

The competitive benchmark rating data we use is Keynote's GomezPro Scorecard (GPSC) ratings of e-service quality for B2C e-channels. GPSC ratings are well-accepted in practice (Carpenter 2005) and often-used in research (Chen and Hitt 2002, Kotha et al. 2004). They pertain to the B2C websites of companies in the retail and financial services sectors. They are developed based on how customers evaluate IT-related determinants of e-service quality pertaining to the following website dimensions: functionality, ease of use, privacy and security, and quality and availability (see Fig. 1). These dimensions map well to multidimensional metrics that have been validated by prior academic research (Devaraj et al. 2002). GPSC ratings are computed as a weighted average of normalized values on a 1-10 scale, with the weights being 40% for functionality, 35% for ease of use, 15% for privacy and security, and 10% for quality and availability. GPSC benchmark ratings are published bi-annually for all sectors (except for two sectors for which they were published quarterly in 1999). The first set of ratings was published in April 1999 for the discount brokerage sector. Later ratings were published also for the banking, full-service brokerage, insurance, mortgages, and credit card services sectors.

We use five years worth of GPSC data, representing the period from early 1999 to the end of 2004. After 2004 the GPSC rating lost its third-party objectivity when the company producing them was purchased by Keynote, a firm that also offers consulting services to rated firms seeking to improve their e-service quality ratings, and the rating methodology has been changed (Wright and Dawson 2004). There are a total of 64 GPSC publication dates made for the six financial services sectors listed above. In total, 168 firms across the six sectors were rated by GPSC, but we refined this list based on the following criteria. First, firms not traded on the New York Stock Exchange or NASDAQ are excluded. Second, the first inclusion of a firm in the GPSC ratings is deleted if that firm's stock was not traded at least sixty days prior to the respective GPSC publication. Last, firms were deleted if the GPSC publication date is confounded by other firm-specific major event (e.g., quarterly earnings announcements, merger and acquisition announcements, stock splits). After applying these criteria the sample was reduced to 102 firms, with a total of 809 usable (firm, published rating event date) pairs.

Table 1 offers summary statistics for the firms' GPSC ratings in our data. The ratings, R_t , fall between 3 and 8 (on a 1–10 scale), with the mean around 5. The relative changes in GPSC ratings from one period to the next, ΔR_t , vary across sectors but their means are close to zero for all sectors. Finally, the frequency of GPSC rating upgrades ($R_t > R_{t-1}$) and downgrades ($R_{t-1} > R_t$) from one period to the next appear to be reasonably balanced.

Table 1 also offers descriptive statistics for the firms rated by GPSC based on other data. These other data include daily stock returns for individual firms and the risk-free rate, represented by the 30-day Treasury bill rate obtained from the CRSP database, and financial firm data (e.g., total assets, book value) obtained from the COMPUSTAT database. The firms rated by GPSC vary in size and in their growth prospects, with a market-to-book value ratio as low as 0.14 (low-growth prospects) and as high as 22.78 (high-growth prospects). These figures suggest that the GPSC announcements we use pertain to a heterogonous set of firms.

Table 1

Descriptive statistic of GPSC ratings and the rated firms.

		Sector						
		Banks	Credit cards	Discount brokerage	Full-service brokerage	Insurance	Mortgages	
No. announcements		12	11	14	9	8	10	
GPSC rating (scale 1–10)	Min. Avg. Max. Std. dev.	3.21 5.79 7.61 0.837	3.29 4.83 6.85 0.734	3.25 5.79 7.99 0.961	4.10 5.80 7.48 0.833	2.68 5.88 7.80 1.011	3.12 5.12 7.94 1.062	
Relative change in GPSC rating	Min. Avg. Max. Std. dev.	-0.338 0.024 0.477 0.096	-0.355 -0.010 0.279 0.099	-0.751 0.011 2.732 0.087	-0.149 0.013 0.22 0.078	-0.327 -0.004 0.202 0.101	-0.328 0.037 0.8 0.177	
Distribution of Gomez score upgrades and downgrades	Upgrade Downgrade No change Total	135 84 7 226	64 83 5 155	90 117 7 214	25 29 7 61	31 27 5 63	48 31 11 90	
No. firms		23	20	21	11	12	15	
Total assets (\$M)	Min. Avg. Max.	116 203,001 1436,554	372 289,330 1453,628	22 208,782 1457,933	2381 476,576 1436,389	168 163,312 724,154	35 159,454 1317,591	
Market-to-book value ratio	Min. Avg. Max.	0.762 2.322 7.200	0.225 3.061 30.456	0.211 4.056 18.162	0.846 2.628 6.642	0.891 2.891 12.149	0.396 2.203 5.883	

4.2. Event study data analysis

The impact of published GPSC ratings on the value of rated firms can be established using an event study. The events of interest are the unexpected relative changes in the GPSC ratings assigned to individual firms. To estimate stock returns in the absence of these events, daily stock returns are regressed against daily returns on a composite market index based on the capital asset pricing model. This is given by $\hat{r}_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t}$, where $\hat{r}_{i,t}$ is the estimated stock return on day t in excess of the risk-free rate $r_{f,t}$; $r_{m,t}$ is the daily return on the market portfolio in excess of $r_{f,t}$; α_i and β_i are firm-specific capital asset pricing model parameters; and ε_{it} is a random error term for firm *i* on day *t*.⁸ The market model is estimated for each (firm, event date) combination using 250 daily returns, starting 253 trading days before the event date,⁹ with the market portfolio being a weighted composite index formed by combining stocks traded on the New York Stock Exchange, the American Stock Exchange, and NASDAQ. The abnormal return for a given firm and announcement date is computed as the difference between the observed returns and that predicted by the generalized autoregressive conditional heteroskedasticity (GARCH) market model (Chatterjee et al. 2002), as follows: $AR_{i,t} = r_{i,t} - \hat{r}_{i,t}$.

We compute *abnormal returns* (ARs) starting three days before an event (-3) and ending three days past the event (+3), as well as *cumulative abnormal returns* (CARs) for the various respective event windows. The longest event window, denoted by [-3, +3], allows us to capture the impact of a change in e-service quality on

Table 2

CARs of relative changes in GPSC's e-service quality ratings.

Day/ window	Ν	Mean (cumulative) abnormal returns (%)	Positive:negative	Patell's Z	Generalized sign Z
-3	809	-0.08	371:438	-1.413	-0.936
-2	809	0.35	460:349	3.889***	5.330***
-1	809	0.44	428:381	3.184***	3.077**
0	809	0.21	430:379	2.699**	3.218***
+1	809	0.20	458:351	3.435***	5.189***
+2	809	0.16	402:407	3.005**	1.247
+3	809	-0.03	382:427	-0.108	-0.161
[-2, 0]	809	1.00	470:339	5.175***	5.612***
[-2, +1]	809	1.19	485:324	6.061***	6.559***
[-1, 0]	809	0.65	456:353	4.160***	5.049***
[-1,+1]	809	0.85	470:339	5.380***	6.034***

** Statistical significance at the 0.01 level using a two-tail test.

*** Statistical significance at the 0.001 level using a two-tail test.

investors' perceptions of a firm's value, because it can account for leakage of information before an announcement and for a slow market response to the announcement. We test the significance of ARs and CARs using two-tailed tests of Patell's Z-statistic and the generalized sign Z-statistic (Cowan Research 2007).¹⁰ The latter test adjusts for the normal asymmetric proportion of positive and negative abnormal returns. Two-tailed tests are used since we hold no expectation on the sign of ARs and the proportion of firms that may be favored by relative changes in GPSC ratings.

Table 2 presents the univariate analysis results of mean ARs and mean CARs. The results support the assertion that announcements (publications) of GPSC ratings convey significant information to the investor community regarding relative changes in e-service quality of B2C channels of financial services firms. Considering the

⁸ Conventionally $\varepsilon_{i,t}$ is assumed to be normally distributed. Yet, with research which shows that the daily stock returns exhibit an autoregressive heteroscedastic error pattern, failure to adjust for conditional heteroscedasticity may compromise the quality of the statistical inferences (Corhay and Rad 1996). Indeed, for our sample data, the market model's residuals using the Lagrange multiplier approach give strong evidence of ARCH errors in over 25% of the cases. We hence adjust the market model for conditional heteroscedasticity by using a GARCH (p = 1, q = 1) model, where p is the order of the autoregressive lag and q is the order of the mosing average lag. Empirical finance research on daily returns data has shown that the simple version of GARCH (1, 1) is adequate to account for conditional variance and performs better than any higher order of GARCH with p + q > 3 (Corhay and Rad 1996).

⁹ We also tried using 180 daily returns in order to avoid the possibility of overlap between GPSC announcements (which occur bi-annually) and to perform a robustness check. The results were not quantitatively or statistically different.

¹⁰ We saw no need to use the portfolio statistic instead (Brown and Warner 1985), even though small subsets in the sample data exhibit the characteristics of clustered events. The reason is that there are 64 GPSC announcements, where only the events pertaining to a single GPSC announcement may potentially exhibit the characteristics of clustered events.

Table	3
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Estimation of Factor Sensitivities.

Variable	Model-1 for estimati sensitivities	ng factor		Model-1.1 for robustr firm-specific control v	ess testing (a variables)	adds two	Model-1.2 for robustr only the control varia	ness testing (bles)	contains
	Parameter estimate	t-value	$\Pr > t $	Parameter estimate	t-value	$\Pr > t $	Parameter estimate	<i>t</i> -value	$\Pr > t $
Intercept	-0.367	-1.83*	0.0681	-3.377	-5.37***	<.0001	-3.158	-4.86***	<.0001
Sensitivities									
β^1 (banks)	5.442	0.89	0.3756	6.866	1.15	0.2484			
β^2 (brok. discount)	12.127	5.12***	<.0001	12.766	5.57***	<.0001			
β^3 (brok. full service)	1.806	0.10	0.9212	-0.805	-0.05	0.9637			
β^4 (credit cards)	20.929	4.66***	<.0001	24.374	5.58***	<.0001			
β^5 (insurance)	0.968	-0.10	0.9203	4.767	0.51	0.6117			
β^6 (mortgages)	4.894	2.00**	0.0453	4.212	3.24***	0.0012			
Control variables									
β^7 (firm size; ln TA)				0.156	2.32**	0.0207	0.146	2.10**	0.0357
β^8 (firm growth; ln MBV)				1.693	7.39***	<.0001	1.509	6.42***	<.0001
N	809			809			809		
R^2	0.062			0.124			0.051		
Adj. R ²	0.055			0.115			0.048		
F-value	8.83***			14.18***			21.60***		
$\Pr > F$	<.0001			<.0001			<.0001		

* Significance at the 0.1 level (two-tailed).

** Significance at the 0.05 level (two-tailed).

**** Significance at the 0.01 level (two-tailed).

statistical significance level of Patell's *Z* test and the generalized sign *Z* test, the mean ARs are different than zero only between day -2 and day +1. This indicates that the only days with significant observed changes in firms' market value are between day -2 and day +1. Table 2 shows the mean CARs only for the event windows that are defined by these days. Based on both statistical tests, all these mean CARs are different than zero at a high statistical significance level.

4.3. Estimation of risk pricing parameters

To price e-service quality risk, we ran two regressions. We first estimated the firms' sensitivities to e-service quality risk by regressing a version of Eq. (1') that is adapted to our data. The dependent variable is CAR[-2, 1], as the CAR for event window [-2, 1] best captures the impact of GPSC ratings among the various event windows we considered (see Table 2). The independent variable is the relative change in the GPSC rating from its expected value, ΔR_t . If a firm is rated for the first time at publication time *t*, a proxy rating for the immediate prior time is taken to be the median rating of all firms rated in publication time *t*-1.

Given that our data covers firms from six different financial services sectors, we assume that firms in one sector have similar sensitivities to relative changes in their benchmark e-service quality ratings. This means that we need to run for each sector a separate regression of Eq. (1'), or run a single cross-sectional pooled regression of Eq. (1'). We tested statistically whether there are any problems that would advise against the latter approach but found none.¹¹ Hence, using the following cross-sectional pooled regression is well justified, and we will refer to it as Model-1:

$C_{int} = \infty + p_1(\Delta R_{it}) + \cdots + p_6(\Delta R_{it}) + 0$ (would	(Model-1)	$(6) + \mathcal{E}_{i}$	$-\beta_6([\Delta R]_{it})$	$_1) + \cdots$	$([\Delta R]_{it})$	$+\beta_1$	$a_{i,t} = \alpha$	CAR _i
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In this expression, $CAR_{i,t}$ is the cumulative abnormal return for the *t*th GPSC published rating for firm *i*; α is the model intercept; β_s is the sensitivity of financial services sector *s* to e-service quality risk; $[\Delta R]_{i,t,s}$ is the relative change in the *t*th GPSC rating for firm *i* if firm *i* is in sector *s*, or 0 otherwise; and $\varepsilon_{i,t}$ is the error term. Since the $[\Delta R]$ predictors have zero expected values, the coefficients β_1 to β_6 are the free parameters being estimated as the sector-specific sensitivities to relative changes in e-service quality.

The left columns of Table 3 show the results of a pooled regression of Model-1, where the mean square errors of the GARCH-based market model estimated by the event study are used as weights to minimize the bias (Cochrane 2005). Risk factor sensitivities are statistically significant for only three sectors: the sensitivity for discounted brokerages is 12.127 (p < 0.0001), for credit cards is 20.929 (p < 0.0001), and for mortgages is 4.894 (p < 0.05). The regression of Model-1 is statistically significant, with an *F*-value of 8.83 (p < 0.0001) and an R^2 of 6.2%.

We performed several checks to test the robustness of the estimated factor sensitivities. First, we controlled for two firm-specific characteristics that may influence the magnitude of CARs, to try to disentangle the primary effects of factor sensitivities from secondary effects of firm-specific characteristics.¹² The firm-specific characteristics we consider from studies that used them in similar settings are firm size and firm growth (Chatterjee et al. 2002, Subramani and Walden 2001). We also ran Model-1.1, which adds to Model-1 the terms $\beta_7(\ln[TA]_{i,t,s})$ and $\beta_8(\ln[MBV]_{i,t,s})$. Here, β_7 and β_8 are regression coefficients, and [TA]_{*i*,*t*,*s*} and [MBV]_{*i*,*t*,*s*} measure firm size and firm growth as the total assets (in \$M) and the market-tobook value ratio, respectively, for firm *i* on the *t*th GPSC rating date if firm *i* is in sector *s*, and 0 otherwise. Both are log-transformed to avoid having a few extreme observations drive the results (Dekimpe et al. 1997). We also ran Model-1.2, which uses only the firm-specific characteristics, based on the terms $\beta_7(\ln[TA]_{its})$ and $\beta_8(\ln[MBV]_{its})$.

The results for these models, shown in the right columns of Table 3, suggest the following. First, and most importantly, factor sensitivities in Model-1.1 are comparable to those in Model-1 in terms of statistical significance and relative magnitudes. Second,

¹¹ While the same factor sensitivities will be obtained using a single cross-sectional pooled regression or separate regression runs for each section, a key advantage of pooling cross-sectional data is the ability to leverage the available degrees of freedom to estimate a larger number of coefficients in a single regression run. But a pooled regression is feasible only if the sections pooled are homogenous (Gould 2005). If not, the pooled regression would enforce the same residual variance for all groups, thereby leading to inadvertent interpretation of the coefficients' statistical significance. Thus, we checked the feasibility of pooling using two statistical tests. We ran Bartlett's (1937) *M*-statistic test and found that the residual variances from separate subsample regressions (for each sector separately) are not statistically different. Based on DeShon and Alexander's (1996) rule of thumb, the ratio between the largest and smallest residual variance should be below the 1.5 threshold, which is what we observed. So both tests support the use of a single pooled regression run.

¹² In line with our primary objective – estimating risk pricing parameters – we do not consider models including interaction effects.

Table 4Estimation of risk premium.

Variable	Model-2 for estimating risk premium					
	Parameter estimate	t-value	$\Pr > t $			
Intercept	0.974	1.42	0.1569			
λ (risk premium)	0.112	2.78***	0.0057			
N	459					
R^2	0.0154					
Adj. R ²	0.0133					
F-statistic	7.18***					
Prob > F	0.0076					

*** Significance at the 0.01 level (two-tailed).

the positive effects of firm size and firm growth are significant and may be a direct result of the relatively large stock return from large firms and firms with rapid growth; yet, the magnitude of coefficients for these effects is smaller than that for factor sensitivities. Last, it turns out that the R^2 s for Model-1 and Model-1.2 almost add up to the R^2 of Model-1.1. This suggests the presence of only weak interactions between the estimated factor sensitivities and the firm-specific characteristics used as controls. Overall, these results indicate the robustness of the estimated factor sensitivities.

In another robustness check, we checked for the possibility that different sectors react to relative changes in e-service quality ratings over different time windows. We regressed Model-1 while varying the dependent variable, CAR, for different time windows ranging from day -2 to day +1. The results (not shown for brevity) were similar. The same three sectors have statistically significant factor sensitivities and these sensitivities retain their relative magnitudes.

To estimate the other risk pricing parameter – the risk premium per unit exposure to e-service quality risk – we regressed CAR[-2, 1] against the sensitivities from Model-1 (Cochrane 2005). We refer to this regression as Model-2:

$$CAR_{i,t} = \alpha + \lambda \beta_{i,s} + \varepsilon_{i,t}$$
 (Model-2)

In this model, α is the intercept, λ is the estimated premium return per unit exposure to e-service quality risk for firms in all sectors, and $\beta_{i,s}$ is the sensitivity for firm *i* in sector *s* set to β_s . Model-2, however, is regressed only for firms in those sectors for which sensitivities came out statistically significant. And, again, to minimize the estimation bias, we use the mean square errors of the GARCH-based market model as weights. Table 4 shows the results. The regression is statistically significant with an *F*-value of 7.18 (p < 0.01). The risk premium λ is 0.112 and is statistically significant (p < 0.01).

5. Discussion

We proceed to interpret the main risk pricing results of e-service risk for financial services firms, present implications for research and practice of these results and the risk pricing approach presented, and highlight limitations of our work and directions for future research.

5.1. Main results and interpretation

One of our main empirical results is that the exposure of firms' B2C e-channels to e-service quality risk is significant. The abnormal returns recorded after the publication of competitive benchmark ratings of firms' e-service quality tell us that some firms benefit while others suffer as a result of these ratings. On the whole the mean abnormal returns are somewhat positive, rather than being zero as if the market reaction to competitive benchmark ratings were following a zero-sum game. One explanation, which is supported by our data, is that the market also rewards a consistent overall improvement in firms' *absolute* e-service quality ratings

resulting from a continued ongoing investment in IT-related determinants of e-service quality.

Another main result is that the sensitivity of financial services firms to e-service quality risk varies across sectors. Firms in three sectors have statistically significant but different sensitivities to relative changes in e-service quality. Credit card firms have the largest sensitivity, followed by discount brokerage and by mortgage firms. This pattern could be due to the rate at which e-services have been embraced in these sectors. Among the most successful early e-commerce businesses were discount brokerage (Bakos et al. 2005) and online mortgage services (Hunt and Menon 2006). E-services in these sectors grew fast, in part, because of the fierce competition and aggressive customer acquisition tactics (Chen and Hitt 2002) from new entrants in the discount brokerage sector (e.g., eTrade, Datek, AmeriTrade) and the mortgage sector (e.g., E-Loan, LendingTree, Floan). The credit card and mortgage sectors faced other growth drivers (Osho 2008). Beginning in 1996, traditional banks pushed to expand their product offerings and customer base on loan products like credit cards and mortgages (Osho 2008). One reason is the erosion of margins in their liability businesses (savings, money market, etc.) due to the emergence of loan aggregators and Web banks. Another reason is that Internet companies with strong brands and highly trafficked websites (e.g., Microsoft, Intuit, Yahoo!) began earning fees for generating mortgage and credit card leads (Hunt and Menon 2006), and the concern was that they would move into fulfillment and funding (HFI June 1997). Lastly, there was also a concern that the Internet will increase the transparency and accelerate concentration among originators (Morgan Stanley Dean Witter 2000). The end result consequence was that e-service quality became a crucial determinant of differentiation (Bakos et al. 2005, Chen and Hitt 2002).

By contrast, the other three sectors were not found to have statistically significant sensitivities to e-service risk. While we cannot make reliable inferences about these sectors, we can speculate about the reasons. Banking, insurance and full-service brokerage services are the largest sectors in the financial services economy (Bakos et al. 2005). The sheer size of these sectors may be at the root of the slow growth in their e-services. These sectors encompass many large traditional firms that are better characterized by their brick-and-mortar side of the business. Their business is inherently about relationships with customers, but at the time, the e-service channels probably did not represent an acceptable substitute for the conventional sales channels. Moreover, the potential for channel conflicts was significant. This factor was at the core of the full-service brokerages' slow responses to competition from the discount brokerages (Bakos et al. 2005). For similar reasons, major commercial houses including JP Morgan and Chase (when they were separate firms) and Bankers Trust did not consider moving into e-services until 1998 (Osho 2008). The insurance sector faced an additional challenge. While considerable growth occurred with commodity-type (motor, travel, and home) insurance products, growth in sales of more complex insurance products could not occur before their lengthy online application process and the need for an offline verification and approval were reengineered (Hunt and Menon 2006).¹³ These factors limited the value of e-service channels, and made firms in these sectors insensitive to e-service quality risk.

This explanation is consistent with the extant research and calls for additional research into the influence of market growth. In the context of new service and e-service entry, the market growth rate

¹³ The mortgage sector dealt with this challenge faster: one firm saw improvements in conversion rates after reducing the loan application form from 16 to 6 steps, and another that redesigned the mortgage application form specifically for the Internet saw the time required to fill in the form reduced to 20 min (Hunt and Menon 2006).

has been observed to have a positive relationship with firm performance (Geyskens et al. 2002, Bowman and Gatignon 1995), as it can characterize the ease of gaining access to a market (Geyskens et al. 2002, Ramaswamy et al. 1994). Because rapid market growth also offers opportunities to broaden e-service operations, it may positively enhance the overall performance improvement that is anticipated due to firms' improvement in their e-service quality ratings. Future research should verify this explanation by controlling for important firm-specific characteristics, for example, the e-service share of a company's entire business. This characteristic probably tends to be low for those sectors for which we did not find a significant level of sensitivity to e-service quality risk.

A third main result comes out of our robustness test. It shows the market reaction observed in connection with changes in e-service quality ratings to be stronger for high growth firms and for large firms. Two factors may explain the relationship with firm growth. On the one hand, high growth companies may have greater opportunities to capitalize on relative improvements in e-service quality ratings due to their earlier IT investments; IT investments are known to have a strong positive complementarities effect with e-commerce capability that positively contributes to firm performance (Zhu 2004). On the other hand, high growth firms experiencing a relative drop in their e-service quality ratings may be constrained in their ability to make the IT investments necessary to recover their relative e-service quality ratings, because growth imposes greater cash flow demands (due to the existence of many high NPV projects) and leaves less funds for IT budgets (Dewan et al. 1998). Both possibilities suggest that high growth firms could be more sensitive to e-service quality risk.

It is puzzling, however, that the market reaction to changes e-service quality risk may be stronger for large firms. Some research has shown that firm size is negatively associated with the market reaction to e-service launch initiatives (Lin et al. 2007). Large firms are less exposed to small changes in any single risk factor, including e-service quality, because they are generally better diversified in relation to their products, services and sales channels. Moreover, large firms often have greater established industry experience, which means a better-established customer base and brand name as well as lower risk (Gatignon et al. 1990, Geyskens et al. 2002). By contrast, small firms stand to lose more from exposure to any single risk, including e-service quality risk, although they may also stand to make inroads into opportunities that larger firms have already exploited, such as extending their geographic reach (Alba et al. 1997, Geyskens et al. 2002). Our result goes against both assertions concerning the impact of firm size, and so more research is needed to verify and explain this result.

5.2. Implications for practice and research

The implications of our work for practice and research are numerous. On a practical level, risk pricing information of the kind we derived can aid managers making decisions on investments in IT-related determinants of e-service quality. Qualitatively, our results suggest that small firms, especially in fast-growing industries, stand to gain more from relative improvements in their e-service quality ratings. Quantitatively, for credit card companies, return on IT investment in e-service quality may be twice as high as that of discount mortgage firms and almost five times that of mortgage firms, at least for the timeframe our data covers. Repeating our analysis with recent data may yield relative return on investment figures that apply today. This information could be of greater value to large financial services firms with business units operating in multiple different sectors (credit card, mortgages, brokerage, etc.), as their investments in IT determinants of e-service quality could be allocated more optimally across units. Going a step further, risk pricing information could also benefit firms seeking to manage their relative e-service quality standing according to benchmark ratings. The premium return on a one-unit change in relative e-service quality ratings is computed as *risk premium* × *sensitivity to risk*. For example, with the risk premium of 0.112% we obtained, the premium return for mortgage firms is $0.112 \times 4.894 = 0.548\%$, for discount brokerage firms is 1.358%, and for credit card firms is 2.344%. Multiplying the premium return by the number of outstanding shares of a firm, *premium return* × *number of shares*, can approximate the gain (or loss) in market value that a firm can expect to see from a one-unit improvement (or drop) in its relative benchmark e-service quality ratings. It remains to be seen, however, whether such an approach also reflects the long-term return on investments in IT-related determinants of e-service quality.

For research, the implications of our work are twofold. Compared to prior research linking individual IT-related determinants of e-service quality to firm financial performance (Anderson et al. 2004, Barua et al. 2004, Chen and Hitt 2002, Kotha et al. 2004), our work goes further by pricing the risk associated with those determinants. It prices e-service quality risk in terms of the economic consequences for a firm if the IT determinants of e-service quality fall behind or move ahead relative to the competition. This can open up new ways for IT and marketing research to think about the economics of investments in e-service quality. Second, the well-established risk pricing approach we presented could work equally well in the context of other idiosyncratic IT investment risks. Security risk, customer adoption risk, and technology maturity risk are just a few of the IT risks that should be of great interest to academics and practitioners. As we mentioned earlier, another adaptation of the approach has been presented and applied elsewhere for the case of pricing software development risks (Benaroch and Appari 2010).¹⁴ Going beyond the pricing of single IT investment risks, though, availability of risk pricing information could open new research directions on fundamental IT investment management problems, including the valuation and ranking of IT investments, the economic-based management of IT investment risk, and the management of IT investment portfolios.

5.3. Limitations and future research

Our study has several limitations which future research ought to try to resolve. First, as we explained earlier, our data sample stops at the fourth quarter of 2004 primarily because of a concern over the objectivity of the third-party ratings posted at that point in time. As a consequence, to obtain a sufficient size data set we have included data from two different periods, before and after the dotcom bust, but we did not control for the possibility of a shift in stock market returns due to the dotcom bust (Dehning et al. 2004). Considering that our goal is one of estimating risk pricing parameters, rather than testing hypotheses, adding time dummies for the before and after dotcom bust periods is not an adequate solution. Rather, it would be necessary to split the data into two

¹⁴ After showing that APT's tradability assumption is neither valid nor necessary for non-traded software development projects, Benaroch and Appari (2010) use an adaptation which assumes that all project managers estimate the cost of their projects using the same software development costing model (e.g., COCOMO, SLIM and SEER). The multi-factor model is adapted to account for firm-specific software development risk factors and for the premium cost they command as a percentage of the project cost predicted by the software development costing model. In this sense, the software development cost estimation model fills the role of a capital market in governing the project cost premium attributable to risk. This adapted approach has also been applied with COCOMO-based data on historical software development projects, to derive benchmark risk pricing parameters for several risk factors. The authors show that the estimated benchmark risk pricing parameters can be used to adequately adjust the project cost. The authors also discuss other uses of risk pricing information in the software development context.

subsamples, before and after the dotcom bust, and replicate the analysis for each subsample separately. Our overall data sample was insufficiently large to create both subsamples.

A second limitation is the relatively low R^2 value that we obtained for the estimation of the risk premium parameter (Table 4). While this R^2 is well within the range of results reported in financial research dealing with risk pricing (Stickel 1992, Schadewitz and Kanto 2002), the skeptics may argue that the observed significance of the coefficients estimated in this regression could be due to sample size as much as it could be due to the presence of a meaningful relationship in the data.

Last, our data set does not include the granular components of Keynote's GomezPro ratings of e-service quality: the ratings for website privacy and security, functionality, ease of use, and information content and quality. Our empirical analysis cannot tell us how much each component alone contributes to the sensitivity of firms to e-service quality risk.

Future research ought to replicate our empirical effort with data covering a longer period and containing the granular components of competitive benchmark ratings of e-service quality. Some of the granular components of e-service quality ratings are in themselves recognized as separate IT investment risks (e.g., website security and availability). Therefore, replicating our empirical effort for the granular components could lead to more fine-grained and valuable risk pricing information. Of course, it is possible that none of these components on its own generates measurable abnormal market reactions to relative changes in e-service quality ratings.

Additional directions for future research follow from our earlier discussion of the empirical results. One direction pertains to the mean abnormal returns computed for announcements of competitive benchmark ratings. These are positive on the whole, whereas one would expect them to be zero (or close to zero) if the impact of changes in relative e-service quality ratings followed a zero-sum game (Table 2). One possibility that we did not mention earlier is that the market reacts more positively to relative improvements in e-service quality. This possibility deserves further exploration as it may have implications for the validity of the linear risk pricing model that we presented. However, it is worth keeping in mind that financial research may have considered this possibility in other contexts and yet it continues using the same linear model.

Another direction worth exploring is how firm-specific characteristics may influence firms' sensitivity to e-service quality risk. Neither the sensitivities we have derived empirically nor the adapted risk pricing model we presented directly consider this issue. Yet, the results of our robustness test indicate the possibility that, at least, firm growth and firm size may moderate firms' sensitivity to e-service quality risk. Future research should consider using a multi-factor version of the risk pricing model we have presented as one direct way to account for firm-specific characteristics.

In summary, this article is the first to present a risk pricing approach in the IT investment risk context and its application to e-service quality risk. Still, it ought to been seen as only a first step in a journey towards a better understanding of the challenges involved in pricing IT investment risk, as well as a fuller appreciation of the theoretical and practical value of risk pricing information. We are confident that the ideas and results that we have presented will inspire and encourage researchers to join this journey and pursue some of the research directions we have touched upon.

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