MARKUS CHRISTEN and MIKLOS SARVARY*

Theoretical work on the pricing of information reveals that competition between independent information sellers can result in prices that are negatively related to the quality or reliability of the information. The theory argues that when information products are unreliable (low quality), independent products become complements, and competition can increase prices. The goal of this study is to test empirically the theory's counterintuitive predictions with the help of an experimental market based on a business simulation. Information products are market forecasts that are available from different competing information sellers; information buyers use these products to make repeated marketing decisions. Sellers set prices to maximize their profit, and buyers decide from which sellers to buy to maximize their own profit (through their marketing decisions). Buyers and sellers are assigned to one of two quality conditions: high-quality, reliable information and low-quality, unreliable information. The reliability of information products (forecasts) is exogenously set and must be inferred by both buyers and sellers from historical forecasts about another market. The results from this experimental market fully support the theory. After some experimentation, prices converge to levels that are strikingly different between the two quality conditions: Prices are significantly higher when the information sold is unreliable (low quality). Moreover, with few competing sellers of low-quality information, prices are higher than with a single seller or with a large number of competing sellers.

Competitive Pricing of Information: A Longitudinal Experiment

Many firms are in the business of selling information to customers who then use the purchased information for decision making. Market research firms, business analysts, various consulting service providers, and even some medical doctors who specialize in providing diagnosis only are members of the rapidly growing information industry. Although information markets have been around in some form for a long time now (e.g., Reuters was founded in 1850 with a few dozen carrier pigeons), increasingly rapid technological innovation has contributed to their explosive growth in recent years. For example, the management consulting industry has shown an average growth rate of 15% during the past 30 years. Market research and the financial information sectors have had similar, double-digit average growth rates in the previous decades.

Given this growth, it is not surprising that "information marketing" has become an emerging topic in the marketing literature. In the past few years, at least half a dozen theoretical articles have been written on information pricing, and three of these have recently won the prestigious John D.C. Little Best Paper Award.[1] Most of these articles assume a monopolist information seller and find that the price of information is directly related to its value, which in turn is directly related to its reliability or accuracy. In other words, as is usual in most product markets, the price of information is positively correlated to its quality.

Sarvary and Parker (1997) show that moderate competition can reverse the positive price–quality relationship for information goods.[2] In other words, with a small number of

*Markus Christen (e-mail: markus.christen@insead.edu) and Miklos Sarvary (e-mail: miklos.sarvary@insead.edu) are Associate Professors of Marketing, INSEAD. The authors thank Pierre Chandon and participants of the 25th HEC/ESSEC/INSEAD seminar for their helpful comments on a previous draft of this article.

[1]These articles include Sarvary and Parker (1997), Bakos and Brynjolfsson (2000), and Iyer and Soberman (2000). Other marketing articles on information pricing include Chu and Messinger (1997), Bakos and Brynjolfsson (1999), Raju and Roy (2000), Sarvary (2002), Arora and Fosfuri (2005), and Christen (2005). See also Villas-Boas (1994) and Ofek and Sarvary (2001).

[2]The lack of a positive price–quality relationship has been empirically documented in other product categories and remains largely unexplained (see, e.g., Gerstner 1985).

ISSN: 0022-2437 (print), 1547-7193 (electronic)

Journal of Marketing Research
Vol. XLIV (February 2007), 42–56

competing information, sellers' equilibrium prices can be higher for unreliable information than for reliable information. This result is driven by the possibility of combining multiple information products from different sellers to create an even better estimate of the "truth" as long as the different information products are not too redundant. When information is reliable, buyers can rely on a single information product, leading to a choice between competing sellers. In this case, information products are "substitutes." This leads to harsh price competition between sellers, which results in low prices. In contrast, when buyers perceive information products as unreliable but sufficiently independent, they should combine multiple information sources to obtain a more accurate estimate of the underlying truth. This makes competing information products "complements," which leads to mild competition between sellers and to higher prices—even higher prices than what a monopolist seller would charge. However, despite the limited incentive to acquire multiple, high-quality information products, competition between sellers of high-quality information can push the price so low that, even in this case, buyers will consider buying multiple information products. In other words, the equilibrium amount of information purchased may not necessarily differ much between markets with low- versus high-quality information.

Anecdotal evidence from several information product categories seems to be consistent with a negative relationship between information price and quality. For example, in a recent article in *Information Week*, Violino and Levin (1997) report data from an extensive study pertaining to information sellers in the highly volatile information technology sector. Well-known information sellers in this industry include Forrester Research, Gartner Group, and Meta Group, among others, which regularly sell industry reports to their clients on market and technology trends. The *Information Week* study consists of a survey of more than 300 clients (information systems executives) that asks for their assessment of information technology analysts' reports on various dimensions. The survey shows that in the market of high-tech industry reports, it is more the rule than the exception that clients buy several different analysts' reports. For example, the article quotes Forrester Research, which claims that 90% of its clients are also Gartner Group's (a competitor's) clients. Furthermore, there seems to be a consensus among executives that the prices of analysts' reports are high, and all clients perceived the quality of the reports as low in terms of reliability. Sarvary and Parker (1997) provide similar evidence, suggesting virtually no competition among information sellers in the early cellular technology sector. They show demand forecasts for cellular phone services by analysts in the mid-1980s. The forecasts reflect high demand uncertainty in this sector, which is argued to trigger the purchase of multiple forecasts from clients, leading to the lack of competition between information sellers.

Although this anecdotal evidence is suggestive, no empirical study has been carried out to test systematically the counterintuitive theoretical predictions about the effect of competition in information markets. In particular, industry data do not allow for an accurate assessment of market prices; no benchmark is available because in each industry, only a single quality condition is observed. The purpose of this article is to fill this gap and test competitive pricing behavior in comparable environments with different (and controlled) levels of information quality and different levels of competition, while preserving most of the complexity of real-world markets in other domains. Importantly, as in the real world, the purchase of information is a means to an end, namely, making (business) decisions.

We use a longitudinal market experiment built around the MARKSTRAT 3 business simulation (Larréché and Gatignon 1998).[3] The information products to be priced and sold are market-size forecasts for different MARKSTRAT markets (segments). Both sellers (participants in a pricing course) and buyers (managers of MARKSTRAT firms in a marketing course) of information want to maximize their own profits over time; sellers achieve this by pricing their information products, and buyers achieve this by deciding from which sellers to buy market forecasts to make marketing-mix/production decisions. In other words, both prices and quantities are determined endogenously in the experimental market (as they are in real markets). The longitudinal aspect of the experiment enables us to test whether buyers and sellers are able to learn the implications of the quality level over time, causing prices to converge to different levels as a function of information quality.

The results strongly support the theoretical predictions. There is evidence of information sellers' initial price experimentation, but over time, prices converge to levels that are strikingly different between the two quality conditions; specifically, prices for unreliable information (low quality) are significantly higher than they are for reliable information (high quality). In other words, there is strong support for the negative relationship between information quality and price. Furthermore, consistent with the theory, in both quality conditions, buyers tend to purchase multiple information products from different sellers, confirming the subtle interaction between buyers' valuation of information and sellers' strategic pricing.

In additional experiments, we further test the effect of competition on the pricing of unreliable information. When varying the number of competitors, consistent with the theory, we find that prices for unreliable information products are indeed significantly higher with few competing sellers of information than with either only a single seller (monopoly) or a large number of competing sellers.

Next, we summarize the background literature related to information acquisition and use. Then, we elaborate on the theory of competitive information pricing and outline our hypotheses. We go on to describe the experiment and present the empirical findings. We then present several validity tests based on an additional experiment. Finally, we discuss the results and their implications and conclude.

BACKGROUND LITERATURE

A large body of experimental research has studied people's information valuation and acquisition behavior under various conditions (e.g., Rötheli 2001; Schoemaker 1989). A related line of research pertains to the use of sample information to update beliefs (for detailed reviews, see Connolly and Serre 1984; Einhorn and Hogarth 1981;

[3]MARKSTRAT has been used in several empirical studies in marketing (see, e.g., Glazer, Steckel, and Winer 1989, 1992).

Slovic, Fischhoff, and Lichtenstein 1977). These studies examine primarily whether the actual acquisition and use of costly information is consistent with normative (Bayesian and expected utility) predictions. Overall, the existing body of evidence suggests that learning is slow and performance is poor and that both over- and underpurchase occurs depending on the particular situation and context. Most of these experiments confront information users with simple tasks and, importantly, assume that the cost of information is predetermined and fixed. In other words, they do not consider how an information seller would change the price of information as a result of information acquisition and use.

In marketing, there is an important stream of work on the managerial use of external information. The early studies of the 1970s on management attitudes in relation to market research (e.g., Holbert 1974; Krum 1978) have been integrated and conceptually developed in a series of studies by Deshpandé and Zaltman (1982, 1984) and Moorman, Deshpandé, and Zaltman (1993) with survey data. These studies examine more complex decision environments and highlight several important factors that influence the managerial use of market research information, including organizational structure, technical quality, surprise, actionability, and researcher–manager interactions. From our perspective, an important takeaway from this research is that both managers and market researchers systematically assess the perceived quality of information as one of the most important factors in the managerial use of information. Patterson (1995) provides further empirical evidence that quality and price are the relevant choice variables for information products. In a survey of 142 client firms, he finds that the consultants' reputations, their experience, and their fees are the most important choice criteria for choosing management consultants. In summary, although people may not be able to estimate the expected value of information perfectly, existing empirical research suggests that they are sensitive to quality differences.

By focusing on the acquisition and usage of information, existing empirical research cannot provide sufficient insight into the effect of the quality of information products on equilibrium information prices under different conditions. Our main research interest lies not only in the actual purchase behavior of decision makers but also in studying how information markets develop when buyers trade off the cost of information and its value for making decisions, whereas sellers set prices by considering the demand for information and, most important, competition. Specifically, in our study, as in the real world, the cost of information is endogenous in the sense that it is set by competing economic agents and thus is the result of demand and supply factors.[4] We are interested not only in the information-pricing behavior of these agents but also in how prices change information buyers' behavior as predicted by normative decision theory. To attain the objectives of this study, we need a setting with the following characteristics: (1) an information market with both information buyers (users) and sellers, (2) a product market in which buyers use the acquired information to make decisions, and (3) repeated decisions to enable information buyers and sellers to learn from feedback the quality of information and competitor/customer (pricing/buying) behavior.

Market experiments (with a simultaneous consideration of demand and supply) were conducted in other contexts related to information to examine different questions. For example, in a classic study, Sunder (1992) uses such an approach in the context of financial information markets, testing how a stock trader's private information is revealed in asset prices as the trader tries to benefit from this information through trade in the stock market. McKelvey and Page (1990) study similar questions. In general, this study is also related to experiments in behavioral economics, a fast-growing area of research (Ho, Lim, and Camerer 2006). To our knowledge, our market experiment to examine the competitive pricing of information is unique. The next section summarizes the key findings of the theoretical literature pertaining to the pricing of information products and presents the resulting hypotheses.

THEORY AND HYPOTHESES

We define an information product as information that is (1) used in decision making and (2) paid for by the decision maker (see Jensen 1991). Examples include market forecasts and market research, financial and economic data, some media (e.g., news services), professional advice, and consulting services.[5] A notable feature of this product category is that consumers can combine multiple products to arrive at a single, better product. Combining multiple information sources results in a more accurate view of the world, which in turn can improve decision making.

However, the benefit of combining multiple products depends on two fundamental underlying characteristics of the available information goods: their correlatedness and reliability. The more correlated the information products are, the less beneficial it is to combine them. Similarly, for a given level of correlation, the more reliable individual information products are, the less beneficial it is to combine them because the marginal impact of an additional piece of information in revealing the truth is much smaller. In the extreme case of perfect information, there is obviously no incentive to combine different information products.[6]

This possible complementarity of information products creates interesting strategic dynamics between competing firms that are pricing and selling them. The resulting equilibrium prices reflect counterintuitive market outcomes, with several counterintuitive practical implications. In particular, for two competing information sellers and "noncompeting" information buyers,[7] Sarvary and Parker (1997)

[4]For a similar argument in the context of brand choice models, see Villas-Boas and Winer (1999).

[5]This definition excludes some product categories, commonly called "information products." For example, advertising that is not paid for by the decision maker; information technology that is not information per se; or most of media, which typically entertain rather than help in decision making, are not information products.

[6]Various theoretical studies examine how to combine multiple forecasts optimally (e.g., Winkler 1981). In this article, we are not interested in how efficient buyers are in combining information from different sources. As long as the aforementioned basic incentives hold, the theoretical results are valid.

[7]The key assumption here is that the information sold is not "strategic" in the sense that exclusive ownership of information does not lead to a large and sustainable advantage.

show analytically that as long as sellers are not too different[8] and their products are not too correlated,

- equilibrium prices are negatively related to product quality,
- a monopolist is better off inviting a competitor in the market, and
- collusion between competitors increases consumer welfare.

The intuition behind these findings is intriguing. When information products are of high quality and/or are highly correlated, combining multiple products yields little benefit. Buyers can rely on a single source of information, which leads to a choice between competing products, usually in favor of the cheaper alternative. In this case, information products are substitutes, as is the case for most other product categories. In turn, substitution leads to harsh price competition between firms because each firm is trying to get the sale by lowering its price. In contrast, when buyers perceive the information products as unreliable and uncorrelated, a single product has little value, whereas combining two uncorrelated products leads to information of significantly higher reliability or quality. This makes competing information products complements. Under complementarity, firms anticipate that buyers are actually interested in buying a bundle rather than a single good. Instead of cutting price, firms tend to increase their prices to secure the largest possible share from the total price that a buyer is willing to pay for the bundle. This leads to higher prices. In this scenario, prices set in competition are higher than those that a single monopolist would set centrally. If competing information sellers coordinated their pricing, not only would they be better off (as is always the case under cooperation), but buyers would also benefit from it because, in this case, such coordination means lower prices. Finally, the counterintuitive effect of competition disappears as the number of competing sellers becomes sufficiently large. When the number of sellers exceeds the number of information products that individual buyers purchase, the market interaction between sellers shifts to competition between high-quality information bundles, and prices decline.

It is important to realize the subtle interaction between the fundamental characteristics of information (correlatedness and reliability). Correlation and reliability independently cause information products to be substitutes. Conversely, for complementarity, information products need to be unreliable and uncorrelated. Consequently, we study the situation in which information products are largely independent and the number of sellers is small to focus on the more counterintuitive effect of reliability or quality.

These outcomes lead to several concrete hypotheses about prices and quantities in competitive information markets with different quality levels, which we can test in a longitudinal market experiment. The experimental setting also enables us to examine the convergence of information prices over time and to compare prices across different competitive settings. The dynamic evolution is interesting because in our experiment, we neither label the quality of forecasts as "low" or "high" nor suggest the potential value of combining multiple forecasts. Although the theoretical predictions may seem intuitive, it is not clear to what extent a market can learn the subtle interaction between quality and competition—existing research indicates that people perform poorly in information acquisition tasks—or whether Sarvary and Parker's (1997) theoretical model is a valid representation of information markets.

In our subsequent hypotheses, we assume that Sarvary and Parker's (1997) broad conditions hold. In this context, our first and central hypothesis pertains to the equilibrium prices of information as a function of information quality:

H_1: With few competitors and independent information products, prices for reliable information are lower than prices for unreliable information (i.e., information quality is negatively related to the market price of information).

The forces that cause information products to be either substitutes or complements are based on normative decision theory. However, this theory assumes that the buyer incurs a fixed cost for the acquisition of information (i.e., a fixed price). In other words, for the same price, buyers buy more unreliable information. To the extent that equilibrium prices are not constant across the two quality conditions, the foregoing arguments are not sufficient to predict the equilibrium purchase amount of information. A notable outcome of Sarvary and Parker's (1997) model is that in equilibrium, buyers may purchase multiple information products regardless of the quality of information. For unreliable information (i.e., under complementarity), this is no surprise. In such a case, as we argued previously, a single forecast is not valuable for decision making, because it is unreliable. The intuition is more complex when independent information products are reliable. In this case, the decision maker obtains the most value from one forecast. At very low prices, however, it makes sense for buyers to purchase an additional forecast. Although the marginal benefit of this information is low, its price (i.e., its cost to the buyer) is even lower, and therefore it is worth purchasing. In the extreme case of free information, a buyer should obtain all available information products. Thus, our hypothesis with respect to quantities is as follows:

H_2: Conditional on buying information, in the low-quality condition, buyers purchase at least two information products, and in the high-quality condition, buyers purchase more than one information product.

If confirmed, this hypothesis has important implications because it suggests that the quality "type" of an information market cannot necessarily be determined solely by considering the amount of information purchased per customer (number of reports or expert opinions). Observing the purchase of multiple information products can indicate either low prices or low quality.

These first two hypotheses are related to the core predictions of the theory. The remaining three hypotheses address validity tests. They verify whether the observed outcomes are consistent with the concept of equilibrium and are indeed linked to the conditions under which the theory holds. To claim that prices and quantities correspond to an equilibrium, we need to observe convergence of prices over time to stable levels. Both sellers and buyers need to infer the implications of the characteristics of information products for pricing and purchase decisions, respectively. Being unaware of the theoretical predictions, they also need to learn the implications of the properties of their information market.

[8]When there are large asymmetries between competing information sellers, the better one usually drives the others out of the market.

In this article, we do not make an exact prediction about how the market will learn the implications of information quality on prices. However, the support from our experimental market for H_1 and H_2 would be of limited value without convergence to somewhat stable price levels. Learning from market feedback to reach equilibrium is a key issue in behavioral economics (for a review, see Ho, Lim, and Camerer 2006). Thus, we test the following hypothesis:

H_3: In both quality conditions, the price dispersion in the marketplace decreases over time, and prices converge to fixed levels.

Finally, we are interested in testing the boundary conditions of the theory by examining the effect of different competitive market structures while keeping the level of information quality low. In other words, we test whether we can make our core results vanish by changing the market conditions to which these apply. Specifically, we test the following two hypotheses:

H_4: With a single seller (monopoly), prices for low-quality information products converge to a lower level than when there is a small number of competing seller firms.

H_5: The positive effect of competition on prices for low-quality information products disappears when there is a large number of competing information sellers.

EXPERIMENT

Information Buyers: Competing MARKSTRAT Firms

The MARKSTRAT 3 business simulation (Larréché and Gatignon 1998) constituted the basis for our experiment. The simulation was administered in an MBA marketing core course of a major international business school. Course participants (101 students in total) were organized in 20 teams of roughly equal size (5 students per team) and four identical MARKSTRAT industries.[9] Within each industry, 5 teams representing five firms competed with one another. The overall performance of each firm in the simulation was tightly linked to the group members' final grades in the course (25% of students' grade was based on their team's ranking in terms of stock price and other financial indicators).[10]

These MARKSTRAT firms constituted the demand side of our information market. In MARKSTRAT, firms must purchase market forecasts to set marketing-mix variables and production levels. This context is an ideal setup to simulate a market for information, in which information buyers are the MARKSTRAT teams and information products are the market forecasts. The four industries were divided into the two experimental conditions (i.e., two industries were assigned to the high-quality condition, and the other two were assigned to the low-quality condition). We explain the details of the quality manipulation subsequently. Therefore, each experimental condition contained ten information-buying MARKSTRAT firms.

Sarvary and Parker's (1997) model assumes independent information buyers while MARKSTRAT firms compete with one another. However, for the theory to hold, the important assumption is that the information purchased does not represent a strategic advantage for the buyers. As we explain subsequently, this is the case for our experiment in which information products consisted of short-term market forecasts. Firms used these products only for operational decisions (e.g., setting production levels). Furthermore, research shows that competition between information buyers reduces the effect of complementarity on information prices (Xiang and Sarvary 2005). In other words, using MARKSTRAT makes the tests of the theory more conservative because the price difference between low- and high-quality information should decrease with competition between information buyers.

Competing Information Sellers

A different set of MBA students (33 in total), who participated in an elective course on pricing strategies at the same school, was assigned the task of pricing the information products. A particularly attractive feature of the sample was that participants were familiar with the MARKSTRAT world because they all had taken the same core course using the MARKSTRAT simulation six months before the experiment. They were organized into ten groups, or "research firms" (R1, R2, …, R10). Similar to buyer teams, seller teams' grades were based on their relative performance (profit) in selling information (25% of their grade). The top two performers in terms of revenues were also promised a bottle of champagne each. Each seller team was randomly assigned to one of the two quality conditions. This quality level applied to all information products sold by a particular seller and did not change over time. Neither sellers nor buyers were aware of the quality manipulation.

There were five seller teams in each quality condition. Each seller team competed with one or two other seller teams with identical product characteristics, but in each period, it competed with different seller teams from the same quality condition. Because two MARKSTRAT industries were assigned to each quality condition, seller teams would occasionally shift between industries, thus facing different customers. Whereas the sellers changed over time in a given MARKSTRAT industry, a particular buyer always had access to the same number of competing sellers (two in one industry and three in the other industry). We used this change in competitive set to try to limit the sellers' ability to adopt cooperative pricing strategies. Similarly, it prevented sellers from negotiating long-term agreements with buyers. Sellers did not know their next set of competitors and buyers. Similarly, buyers did not know their next set of sellers.

The experimental design has 8 cells—2 quality conditions × 2 product categories × 2 MARKSTRAT industries (different number of information sellers); product category and MARKSTRAT industry represent within-information seller factors. Figure 1 summarizes this experimental setup.

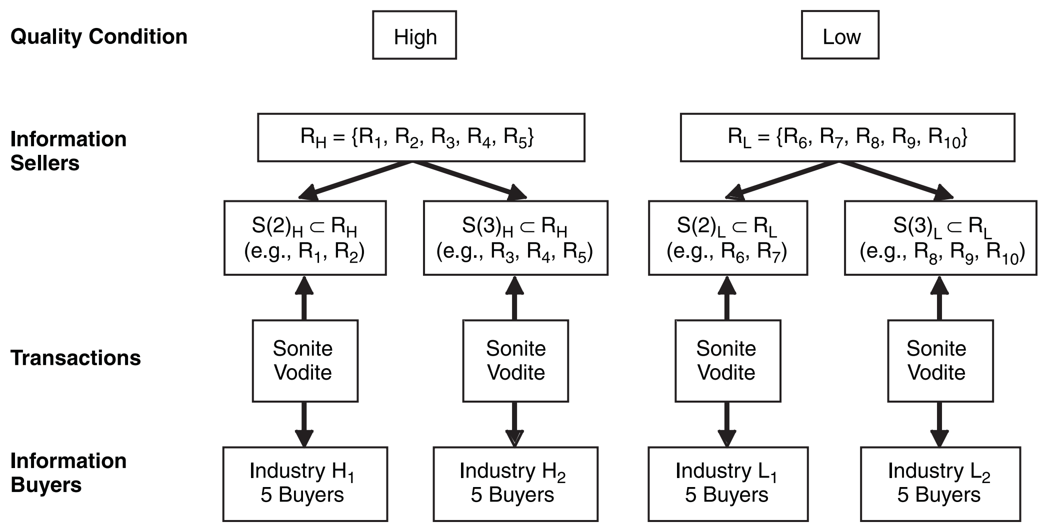
Information Products

In MARKSTRAT, firms compete in two product categories. One (Sonites) is an existing, relatively mature category, in which all competing MARKSTRAT firms participate (at least initially), and the other (Vodites) is a new or emerging product category, in which firms have the option

[9]All MARKSTRAT industries shared the same parameter setting and thus were identical at the beginning of the simulation. However, the evolution of a MARKSTRAT industry over time also depends on the decisions by the competing firms (information buyers).

[10]Another 25% of the grade was based on written reports associated with MARKSTRAT. Moreover, final course grades were based on an overall ranking, which means that grading was competitive.

Figure 1
EXPERIMENTAL DESIGN



Notes: The subsets S(2) and S(3) of information sellers assigned to a MARKSTRAT industry (information buyers) change from period to period. Industries H_1 and L_1 are always served by two information sellers, and industries H_2 and L_2 are always served by three information sellers. Sonite and Vodite denote the two product markets in MARKSTRAT to which the information products refer.

to enter. The Sonite category consists of five segments, and the Vodite category consists of three segments. Each segment grows at a different rate. We grouped the eight one-period market-size forecasts that correspond to each of these segments into three different information products or bundles of forecasts. A first bundle consisted of two forecasts for the fastest-growing Sonite segments, and a second bundle consisted of the forecasts for the three Vodite segments. Each information seller priced and sold these two information products (bundles). Although the forecasts of information sellers within the same quality condition had the same statistical properties (e.g., variance), the actual forecasts provided different figures. The forecasts for the remaining three Sonite segments, which were more mature and thus experienced smaller changes in market size, were available from an "outside" firm. The price of this third bundle was set by the experimenter and was the same across all conditions. Initially, this price was \$15K, but it increased over time with the inflation of the MARKSTRAT world. By the end of the experiment, it had increased to \$25K.

We selected this separation of the various market forecasts for three reasons. First, having sellers price two information products enables us to increase the number of observations (within-seller replication). Conversely, pricing each market forecast individually would have made the pricing task much more complicated and therefore would have increased the noise in the data. Second, the two high-growth Sonite segments and the three Vodite segments experienced rapid changes, which created considerable incentives to purchase information every period. In contrast, the remaining three Sonite segments experienced less change, which limited the need to buy forecasts every period. Third, setting the price of the forecasts ourselves for the three low-growth Sonite segments provided an initial anchor or reference price that was common for all information sellers and buyers regardless of the experimental condition.

Each information product consisted of one-period forecasts only. As such, the information was primarily valuable for operational decisions (e.g., setting of production quantities) rather than for strategic decisions (e.g., whether to enter a new market). To guide strategy, MARKSTRAT teams were given (for free) a qualitative assessment of the expected long-term growth for each market segment. The forecasts available within the MARKSTRAT software were disabled.

Experimental Conditions

As we indicated previously, the four MARKSTRAT industries were assigned to two different information-quality conditions. Neither buyers nor sellers were directly informed whether their information was of high or low quality. Instead, they were provided with a series of numbers for each information-selling firm. They were told that these numbers represented historical demand forecasts the firms made for another market. To be able to evaluate the accuracy of these historical forecasts, they were also given the actual outcomes. These historical forecasts appear in Table 1. This quality information was provided to both sellers and buyers for every decision period with the Information Pricing Form and the Information Ordering Form (see Web Appendixes A and B, respectively, at http://www.marketingpower.com/content84061.php). As such, this quality information was common knowledge. However, both buyers and sellers needed to learn the value of forecasts and the implication of the quality level for information prices.[11]

[11]For the information-buying (MARKSTRAT) teams, the different conditions coincided with different sections of the marketing core course. Thus, they were largely unaware of the manipulation. By the end of the simulation, some information-selling teams knew that there were differences but did not know the nature of the manipulation.

Table 1

INFORMATION QUALITY BY EXPERIMENTAL CONDITIONS: HISTORY OF FORECASTS BY RESEARCH FIRM

A: High-Quality Condition

	Research Firm					
Forecasts	*R1*	*R2*	*R3*	*R4*	*R5*	*Actual*
1	458	483	471	482	444	439
2	488	473	505	483	495	479
3	493	491	467	473	496	464
4	462	489	467	474	463	506
5	486	497	488	498	470	480

B: Low-Quality Condition

	Research Firm					
Forecasts	*R6*	*R7*	*R8*	*R9*	*R10*	*Actual*
1	712	508	926	988	899	843
2	668	723	480	830	869	677
3	841	517	767	659	455	591
4	940	899	876	936	637	824
5	532	724	925	458	889	711

These historical data were created to be consistent with the variance parameters used to generate the actual forecasts, but they had different means. We conducted several pretests to check these manipulations. To ensure that the quality of these forecasts was perceived as equal across the five different information sellers within a quality condition, we conducted a pretest using MBA students from another section who were also enrolled in the same MARKSTRAT course but did not participate in the experiment. On the basis of the pretest, we adjusted the historical data not only to balance the average forecasting error but also to ensure that the best and worst forecasts were somewhat equally distributed across research firms. To achieve this balance, it also became difficult to "signal" the independence between the forecasts accurately. As a result, for the high-quality condition, the empirical correlation of forecasts was .37, and for the low-quality condition, it was .19. However, a second pretest confirmed that participants perceived these forecasts as "independent." In the low-quality condition, several students actually used the term "uncorrelated." In the high-quality condition, the forecasts were perceived as "similar," "redundant," or "the same," independent of correlation.[12]

Actual forecasts were generated by drawing random numbers from a multivariate normal distribution. The variances of the distribution differed between the two quality conditions. For the high-quality condition, we set the standard deviation to 5% of the mean, and for the low-quality condition, we set the standard deviation to 18% of the mean. These standard deviations are consistent with what industry participants would observe in the real world in an uncertain market. The means of the distribution corresponded to the demand forecasts generated by MARKSTRAT.[13] In other words, each forecast for a segment was (usually) a different number, but the statistical properties of the forecasts were identical across information sellers within the same experimental condition. Only the means changed over time on the basis of the evolution of the market segments in the different MARKSTRAT industries.

Given our design, the sample statistics (variance and correlation) of the historical forecasts provided to all participants (see Table 1) and those of the forecasts generated every period in the context of the MARKSTRAT simulation were slightly different. However, participants did not perceive this small difference. In the postexperiment debriefs, no teams raised any issue about inconsistencies across these data.[14]

Procedure: Market Transactions

In each period, the information sellers were asked to price the two bundles of forecasts—two Sonite forecasts and three Vodite forecasts—knowing which MARKSTRAT firms were the potential buyers and knowing which other sellers they were competing against (see the sample Information Pricing Form in Web Appendix A at http://www.marketingpower.com/content84061.php). In addition, they were always given the price of the third bundle of forecasts for the remaining three segments in the Sonite category. (Initially, this price was $15K, and it subsequently increased with MARKSTRAT inflation.) Finally, they received the previous period's prices and unit sales for all five information sellers competing in the same quality condition.

Seeing the different price offers and having access to the information products' reliabilities as indicated by the historical forecasts, buyers could purchase information from any (none, one, or multiple) seller. Web Appendix B (see http://www.marketingpower.com/content84061.php) provides a sample of the Information Order Form, which was submitted with a MARKSTRAT decision to the administrator. MARKSTRAT teams received the purchased market forecasts with all the MARKSTRAT results and data (for a sample, see Web Appendix C at http://www.marketingpower.com/content84061.php). In total, there were seven pricing periods and MARKSTRAT decisions.

After the experiment, all participants were debriefed in groups (buyers and sellers). The debriefing consisted of an open question to provide a rationale for the group's information acquisition/sales strategy. After the debriefings, the experiments were explained to all participants, and the preliminary results were revealed.

RESULTS

The longitudinal market experiment yielded 255 transactions to test our hypotheses. We eliminated the last period (Period 7) because the purchase decisions were likely

[12]Specifically, this second pretest showed participants different sets of low- and high-quality forecasts with low (negative and positive) correlation and with no correlation. No difference was recorded in terms of perceived correlations across sets. This is not surprising given that correlation is the second moment that is not easy to infer from five data points. Debriefs after the experiment also confirmed that participants were concerned about "best" and "worst" forecasts rather than correlation across forecasts.

[13]True demand for a given MARKSTRAT segment depends on the information-buying firms' decisions and thus is not known when the forecasts are made.

[14]Neither sellers nor buyers ever saw a complete set of forecasts from all research firms. First, sellers rarely asked for and hardly ever saw the forecasts. Second, buyers did not have access to the same research firm every period. Third, buyers saw only the purchased forecasts. Thus, the historical data represented the only consistently available quality indication for the information for both sellers and buyers.

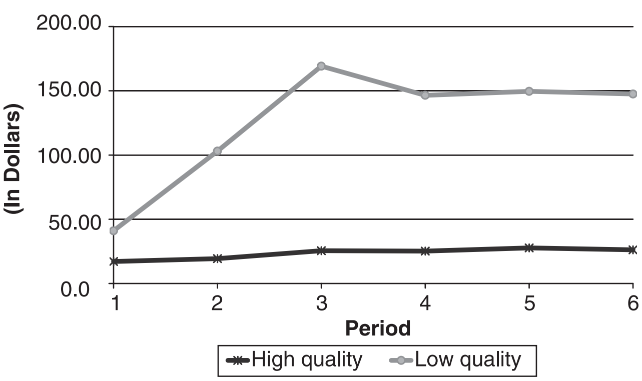
affected by "end-gaming" of buying teams. The dependent variable of interest is the transaction price. In other words, we do not include a price for an information product that was not sold. Average transaction prices in the different quality conditions appear in Figure 2 for the Sonite and Vodite product categories. (Web Appendix D [see http://www.marketingpower.com/content84061.php] shows a summary of all transactions by product category and quality condition.)

The graphs in Figure 2 suggest that the results are in the direction we predicted in H_1. The average prices paid are considerably higher in the low-quality condition than in the high-quality condition. This is true for information products in both Sonite and Vodite product categories. Furthermore, average prices change little after approximately the third decision, which is consistent with markets reaching an equilibrium state. Figure 3, which shows the prices set by the different information sellers, further supports this, indicating that after significant variance among firms during early periods, prices converge to highly consistent levels across MARKSTRAT industries in the same experimental conditions. Next, we report the results from formal statistical analyses to test our hypotheses.

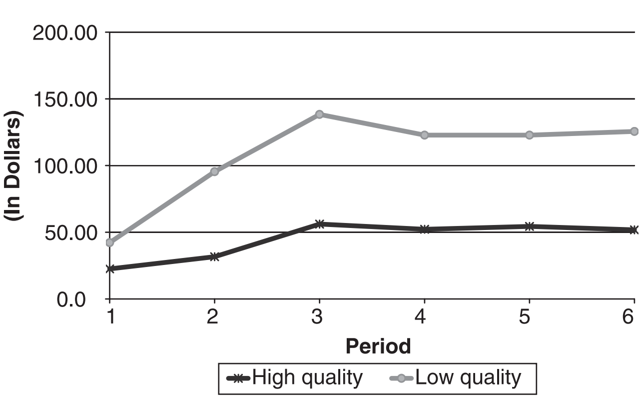
Figure 2

AVERAGE INFORMATION PRICES PAID BY INFORMATION BUYERS

A: Average Prices: Sonite Category



B: Average Prices: Vodite Category



Information Prices

Table 2, Panel A, shows information prices averaged over all transactions for the two quality conditions by product category (Sonite versus Vodite) and MARKSTRAT industry (two sellers versus three sellers). We obtain the most direct empirical test of the theory of information pricing under competition by comparing the prices in MARKSTRAT industries with only two information sellers. The noncentral t-test of the mean prices between quality conditions strongly supports H_1. For the Sonite category, the average prices are 23.8 and 114.6 for the high-quality and the low-quality conditions, respectively. The t-value for the mean difference is 7.23 ($p < .001$). For the Vodite category, the average prices are 50.6 and 102.7 for the high-quality and the low-quality conditions, respectively. Here, the t-value for the mean difference is 4.36 ($p < .001$). Comparing the prices for competition among three sellers or pooling the data across both product categories and MARKSTRAT industries yields the same strong statistical support for H_1 (see the last column of Table 2, Panel A).

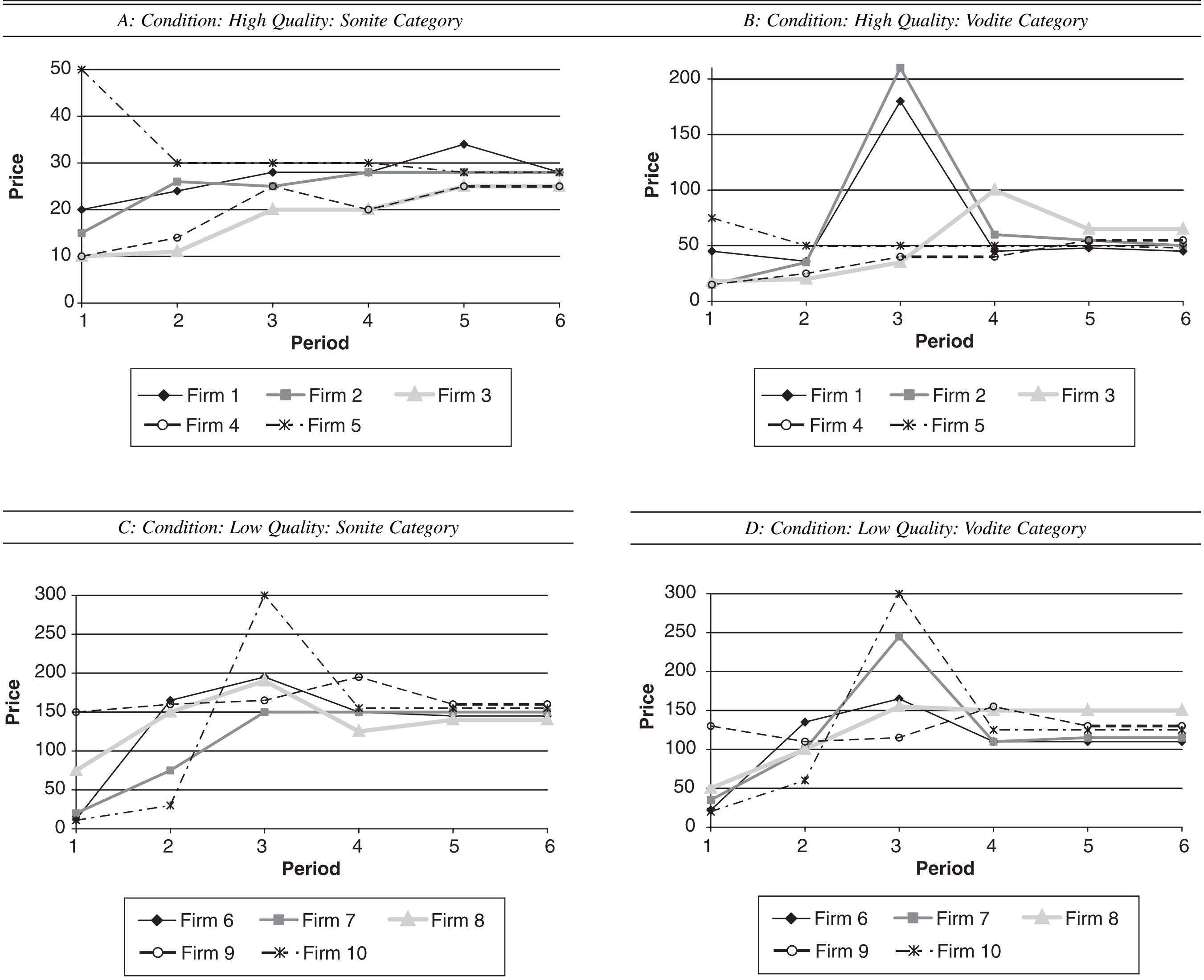
Table 2, Panel B, shows the same results but only for the last three decision periods to eliminate the effect of pricing and buying experimentation that took place in the market during the first few periods. The results show higher mean prices and substantially lower standard deviations. Across all conditions, the average price is 136.5 for low-quality information and 38.9 for high-quality information. The t-value of the mean difference is 32.6 ($p < .001$; see the last column of Table 2, Panel B).

To rule out that this result is an artifact of pooling data across decisions periods, we conducted a period-by-period comparison of the mean prices. This analysis is possible because we can pool the data across product categories and MARKSTRAT industries. In general, F tests did not reject the pooling of data (in particular, not after the first two periods). Table 3 shows the results from this analysis. For all periods, we find statistically significant differences in the direction that H_1 predicted. Except for the first period, this also holds true when we make the comparisons separately for Sonites and Vodites or separately for the MARKSTRAT industries (two sellers versus three sellers). Again, the results in Table 3 show the convergence of prices over time. After the third decision, the changes in average prices are only marginally significant, and the standard deviations are much lower, remain stable, and are the same in both quality conditions.

Although the parameter settings were the same for all four MARKSTRAT industries, these industries evolve somewhat differently over time because industry evolution also depends on the competing firms' (information buyers') decisions. To examine whether such differences could account for our results, we use a regression analysis with several covariates that capture the product-market conditions that the information buyers faced. In addition, we control for fixed effects related to information sellers. The results from this analysis appear in Table 4. Model 1 is a simple "main effects" model and shows that there are no significant differences between product categories or between MARKSTRAT industries. However, Model 2 shows a significant interaction effect for quality and category. As Figure 2 shows, average Vodite prices in the low-quality condition were slightly lower than average Sonite

Figure 3

INFORMATION PRICES CHARGED BY INFORMATION SELLERS



Notes: Some of these prices charged did not result in actual purchases (i.e., they did not become transaction prices).

prices, whereas the reverse was true for the high-quality condition. In Model 2, the parameter estimate of quality indicates the effect of quality for Sonites, not the average or main effect. This explains the much lower parameter estimate in Model 2 than in Model 1 (–93.1 versus –76.3). Model 3 accounts for period-specific effects and shows that the simpler Model 1 sufficiently captures changes over time.

Model 4 is of the greatest interest because it shows that the negative effect of information quality on prices holds even when we control for differences between MARKSTRAT industries and information sellers. The parameter estimate for quality is somewhat smaller (in absolute terms) when we include the covariates and control for seller fixed effects (–65.7 versus –76.3). However, the negative effect of quality remains highly significant. The effects of different MARKSTRAT industry characteristics are not significant. Specifically, Model 4 shows three covariates: the growth of the Sonite market, the extent to which the leading MARKSTRAT firm dominated its industry (ratio of its profit to total industry profit), and total industry profit. We lagged these variables to capture the conditions that prevailed at the time buyers made their information purchase decisions. None of the effects reach statistical significance. (We repeated this analysis with several other covariates and obtained the same results.)

Purchase Quantities

To test H_2 formally, we again conduct a series of statistical tests. H_2 predicted that in the low-quality condition, buyers would purchase at least two information products (if at all), whereas in the high-quality condition, they would purchase more than one information product. To test this hypothesis, we first calculate for each quality condition the mean purchases per firm conditional on a firm purchasing at least one report. This is necessary because the high price of

Table 2

LOWER INFORMATION QUALITY LEADS TO HIGHER PRICES: AVERAGE RESULTS

		Sonite		Vodite		
A: All Periods						
Quality		*Two Sellers*	*Three Sellers*	*Two Sellers*	*Three Sellers*	*Total*
Low	n	25	41	22	40	128
	Average	114.6	112.9	102.7	94.3	105.7
	(SD)	(62.4)	(56.9)	(49.7)	(40.3)	(52.2)
High	n	32	34	29	32	127
	Average	23.8	22.2	50.6	35.3	32.4
	(SD)	(7.73)	(8.65)	(30.2)	(14.6)	(20.4)
t-test[a]	t-value	7.23	10.01	4.36	8.36	14.8
	(d.f.)	(24.6)	(42.2)	(34.0)	(51.6)	(165.2)
	p value	<.001	<.001	<.001	<.001	<.001
B: Periods 4–6						
Quality		*Two Sellers*	*Three Sellers*	*Two Sellers*	*Three Sellers*	*Total*
Low	n	11	19	10	17	57
	Average	145.9	149.2	127.5	121.5	136.5
	(SD)	(13.0)	(5.07)	(14.8)	(15.7)	(17.3)
High	n	16	14	17	10	57
	Average	25.3	27.4	54.6	49.9	38.9
	(SD)	(2.50)	(4.09)	(7.58)	(6.12)	(14.5)
t-test[a]	t-value	30.4	73.8†	14.5	16.8	32.6†
	(d.f.)	(10.5)	(31)	(11.8)	(22.7)	(112)
	p value	<.001	<.001	<.001	<.001	<.001

[a]Noncentral t-test except where indicated by †; *p* values reflect one-tailed t-tests.

Table 3

LOWER INFORMATION QUALITY LEADS TO HIGHER PRICES: RESULTS BY PERIOD

Period	*Quality*	*Average Prices*[a]	*n*	*F Test*[b]	*p Value*	*t-Test*	*d.f.*	*p Value*
1	Low	41.6 (41.0)	34					
	High	19.8 (15.1)	28	7.38	<.001	2.87	43.3	.003
2	Low	99.4 (42.9)	25					
	High	25.2 (11.4)	23	14.1	<.001	8.33	27.7	<.001
3	Low	153.8 (7.81)	12					
	High	40.0 (8.07)	19	.59	.38	9.54	29	<.001
4	Low	135.3 (4.35)	19					
	High	38.4 (3.74)	18	1.43	.47	16.8	35	<.001
5	Low	138.1 (3.69)	21					
	High	40.4 (3.17)	21	1.36	.50	20.1	40	<.001
6	Low	135.9 (4.05)	17					
	High	37.6 (3.24)	18	1.48	<.43	19.1	33	<.001

[a]Standard deviations are in parentheses.
[b]Noncentral t-test when F test is significant; *p* values reflect one-tailed t-tests.

information in the low-quality condition may stop some firms from buying any information.

The results appear in Table 5. The results show that, indeed, the average purchase amount is higher than 1 for both quality conditions. In the low-quality condition, the average number of reports purchased per period and firm is 1.98 reports, which is significantly higher than 1 ($t = 20.2$, $p < .001$). According to H_2, firms that buy a report should buy at least 2 reports. The mean is just below 2, but the difference is not statistically significant ($t = .474$, $p = .64$). The average number of reports differs little between the two information products. On average, firms purchased 1.96 Sonite reports and 2.00 Vodite reports. Over time, the average number of reports varied from a low of 1.625 Sonite reports in Period 2 to a high of 2.25 Vodite reports in Period 6. The average is at least 2 in 9 of the 12 observations (6 periods × 2 information products).

In the high-quality condition, the average number of reports purchased per period and firm is 1.67 reports, which is significantly higher than 1 ($t = 7.60$, $p < .001$). The average number of Sonite reports purchased (1.55) is slightly lower than the average number of Vodite reports (1.77), but both numbers are significantly higher than 1. The average purchase ranges from a low of only 1.25 Sonite reports per

Table 4
LOWER INFORMATION QUALITY LEADS TO HIGHER PRICES: REGRESSION ANALYSIS

Factors[a]	*Model 1*		*Model 2*		*Model 3*		*Model 4*	
Constant	26.5**	(8.54)	35.2**	(8.81)			55.1*	(22.1)
Quality	–76.3**	(3.92)	–93.1**	(6.81)	–77.2**	(3.91)	–65.7**	(8.50)
Category	2.71	(3.90)	–14.9**	(5.29)	2.67	(3.87)	1.03	(3.49)
Industry	–3.88	(3.97)	–3.48	(5.49)	–4.69	(3.97)	–1.50	(4.12)
Quality × category			35.3**	(7.50)				
Quality × industry			–.50	(7.66)				
Period	47.7**	(5.49)	47.2**	(5.29)			34.3**	(3.58)
Period^2	–5.31**	(.80)	–5.24**	(.77)			–3.59**	(1.23)
Period 1					68.1**	(5.39)		
Period 2					102.4**	(5.78)		
Period 3					133.1**	(6.92)		
Period 4					126.5**	(6.08)		
Period 5					129.3**	(5.97)		
Period 6					126.2**	(6.35)		
Growth (lag)							–34.8	(33.1)
Competition (lag)							–10.9	(29.9)
Profit (lag)							–.06	(.11)
Observations	255		255		255		193	
R^2	.675		.702		.684		.819	

*p < .05 (two-tailed t-tests).
**p < .01 (two-tailed t-tests).
[a]Factor coding for analysis is as follows: quality: low = 0, high = 1; category: Sonite = 0, Vodite = 1. The covariates describing the MARKSTRAT industry were lagged by one period and are as follows: growth = unit sales growth for Sonite market, competition = share of industry profit of leading firm, and profit = total industry profit.
Notes: Standard errors are in parentheses. We estimated Models 1–3 with ordinary least sqaures; for Model 4, we used fixed-effects estimation.

Table 5
COMPARISON OF AVERAGE PURCHASE AMOUNTS

		High Quality	*Low Quality*
Sonite	M	1.553	1.958
	SD	.230	.171
Vodite	M	1.774	1.996
	SD	.345	.178
All	M	1.664	1.977
	SD	.303	.167
$\bar{n} > 1$	t-value	7.60	20.2
	p value	<.001	<.001
$\bar{n} = 2$	t-value	3.85	.474
	p value	.003	.644

Notes: We calculated mean period by period conditional on the purchase of at least one report. This leads to six observations for each information product and information quality.

firm in Period 3 (when some research firms set high prices) to 2.25 Vodite reports per firm in Period 4. The average is 2 or more reports in only 2 of the 12 observations. The average number of reports purchased in the high-quality condition is significantly lower than that in the low-quality condition (t = 3.14, p = .005).

Together these results provide strong support for both parts of H_2, including the less intuitive part that even in the high-quality condition, firms would purchase more than 1 report. This is important because it supports the argument that the quality "type" of an information market cannot be inferred simply by examining average purchase quantities.

VALIDITY TESTS

Price Dynamics

With respect to the dynamics of pricing, Figure 3 shows the evolution of prices over time for each product market in the two conditions. Each panel in Figure 3 shows each firm's prices over time and across product categories and conditions. (Figure 2 shows the average prices paid in the marketplace.) Note that price dispersion decreases over time. The variance of prices in the first three periods is significantly higher than the variance of prices in the last three periods. This is formally confirmed with a test on variances. All four F test statistics (2 conditions × 2 product markets) are highly significant (i.e., p < .001). A period-by-period comparison of the prices charged by the information sellers indicates that the reductions in variances from Period 2 to Period 3 and from Period 3 to Period 4 were particularly significant (see Table 3). As we discussed previously in the regression analysis, average prices also increased rapidly until Period 3 and then fluctuated relatively little around somewhat lower price levels than were reached in Period 3. As such, H_3 is strongly supported, suggesting that the market has indeed converged to an equilibrium.

Effect of Competition for Low-Quality Information

The results we presented so far strongly support the main proposition of the theory that with few competing information sellers and independent information products, prices for low-quality information exceed those for high-quality information. This theoretical prediction is based on the possibility of combining multiple pieces of information from different vendors into a single, more accurate piece of information, which can make information from competing firms complementary products. This has two implications for information prices under different competitive market structures. First, no complementarity can exist when there is only a single vendor (monopoly). Second, the complementarity disappears as the number of firms becomes large because the marginal improvement in the quality of information gained from the last firm decreases as the number of competitors increases. These two implications are the basis for H_4 and H_5.

To test these two hypotheses, we repeated the experimental market we described previously, except that we kept the quality of information low and constant across all information sellers and, instead, varied the number of information sellers. Specifically, we used two MARKSTRAT industries. In one MARKSTRAT industry, information buyers had access to only one information seller (monopoly), and in the second MARKSTRAT industry, information buyers had access to five information sellers (strong competition). To be able to compare the results to the previous experiment, we kept everything else the same, including the setup of the MARKSTRAT industries and the quality manipulation. (In the case with only one information seller, the historical data showed the series for only one firm.) The participants were in the same two MBA courses but from new promotions. (All participants in the previous experiment had graduated.)

Table 6 shows the average transaction prices for the three competitive levels and both product categories—Table 6, Panel A, for all periods and Table 6, Panel B, only for the last three periods. The mean prices are all consistent with H_4 and H_5. Prices are higher in the condition with limited

Table 6

A LARGE NUMBER OF COMPETITORS ELIMINATES THE PRICE PREMIUM FOR LOWER INFORMATION QUALITY

		A: All Periods		
Quality		*Sonite*	*Vodite*	*Total*
Monopoly	n	28	24	52
(one seller)	Average	31.3	43.3	36.8
	(SD)	(7.65)	(7.89)	(9.80)
Limited competition	n	66	62	128
(two to three sellers)	Average	113.5	97.3	105.7
	(SD)	(58.6)	(43.5)	(52.2)
Strong competition	n	51	55	106
(five sellers)	Average	23.4	33.0	28.4
	(SD)	(7.91)	(11.5)	(11.0)
t-test[a]	t-value	11.2	9.38	14.3
Limited competition–	(d.f.)	(70.1)	(70.5)	(147.2)
monopoly	*p* value	<.001	<.001	<.001
t-test	t-value	12.4	11.2	16.3
Limited competition–strong	(d.f.)	(68.1)	(70.4)	(140.4)
competition	*p* value	<.001	<.001	<.001
t-test	t-value	4.25†	4.63	4.70†
Strong competition–monopoly	(d.f.)	(77)	(62.4)	(156)
	p value	<.001	<.001	<.001

		B: Periods 4–6		
Quality		*Sonite*	*Vodite*	*Total*
Monopoly	n	13	12	25
(one seller)	Average	38.5	48.3	43.2
	(SD)	(2.40)	(2.46)	(5.57)
Limited competition	n	30	27	57
(two to three sellers)	Average	148.0	123.7	136.5
	(SD)	(8.97)	(15.4)	(17.3)
Strong competition	n	25	32	57
(five sellers)	Average	27.9	38.8	34.0
	(SD)	(6.91)	(10.4)	(10.5)
t-test[a]	*t*-value	63.2	24.8	36.6
Limited competition–	(d.f.)	(37.2)	(28.9)	(75.7)
monopoly	*p* value	<.001	<.001	<.001
t-test	t-value	55.6†	24.4	138.3
Limited competition–strong	(d.f.)	(53)	(44.4)	(92.1)
competition	*p* value	<.001	<.001	<.001
t-test	t-value	6.87	4.87	5.17
Strong competition–monopoly	(d.f.)	(62.4)	(38.6)	(76.9)
	p value	<.001	<.001	<.001

[a]Noncentral t-test except where indicated by †; *p* values reflect one-tailed t-tests.

competition than in the other two conditions. All t-tests comparing the mean prices of limited competition with those in the monopoly condition are highly statistically significant, in support of H_4. Similarly, all t-tests comparing the mean prices of limited competition with those in the strong competition condition are highly statistically significant, in support of H_5. We also compared the monopoly prices with the strong competition prices and found the former to be significantly higher. Although we have no theoretical interest in this comparison, the result is as would be expected, thus lending credence to the validity of our experimental market.

We also conducted a regression analysis using fixed-effects estimation to control for firm-specific (information seller–specific) factors, which are ignored in the simple mean comparison tests we present in Table 6. The regression results appear in Table 7. The corresponding specification tests confirm the findings from Table 6. The average prices across the three conditions are different ($F(2, 272) = 44.8$, $p < .001$). Moreover, the average prices for limited competition are higher than the average prices in the monopoly condition ($F(1, 272) = 67.9$, $p < .001$) and those in the strong competition condition ($F(1, 272) = 71.3$, $p < .001$). The average prices in the monopoly condition are marginally higher than those in the strong competition condition ($F(1, 272) = 3.60$, $p = .059$). These comparisons are based on data from all periods. Again, when we use only the data from the last three periods, the differences become more pronounced, and the statistical significance becomes higher.

Table 7

THE EFFECT OF COMPETITION ON INFORMATION PRICES: REGRESSION ANALYSIS

Factors[a]	*Estimates*
1. Limited competition	14.8*
	(7.04)
2. Monopoly	–35.7**
	(7.06)
3. Strong competition	–48.0**
	(8.28)
Category	3.53
	(3.02)
Period	40.1**
	(4.21)
Period^2	–4.30**
	(.61)
Observations	286
R^2	.769

F Tests	
1 = 2 = 3	$F(2, 272) = 44.8$
	$p < .001$
1 = 2	$F(1, 272) = 67.9$
	$p < .001$
1 = 3	$F(1, 272) = 71.3$
	$p < .001$
2 = 3	$F(1, 272) = 3.60$
	$p = .059$

*$p < .05$ (two-tailed t-tests).
**$p < .01$ (two-tailed t-tests).
[a]Factor coding for analysis is as follows: category: Sonite = 0, Vodite = 1.
Notes: Standard errors are in parentheses. We used fixed-effects estimation.

DISCUSSION AND CONCLUSION

The goal of this article was to test the theoretical model of competitive information pricing that Sarvary and Parker (1997) propose. This model advances a central hypothesis that the reliability or quality of independent information products does not map continuously in the equilibrium prices set by the competing firms that sell these products, as is often the case for other product categories. Instead, changes in the reliability of information may lead to qualitatively different competitive patterns. Specifically, when information products are of high quality, they tend to be substitutes, and equilibrium prices are low. In contrast, when independent information products are of low quality, they are complements, resulting in high prices. In other words, there is a negative relationship between the quality (accuracy) of information and its market price. The results of our experiments strongly support the model's predictions. Prices across different quality conditions and different competitive conditions are significantly different and in line with the theory's predictions. They are also surprisingly consistent across independent markets (MARKSTRAT industries) within the same condition.

A key aspect of our experiment was that we did not directly communicate the characteristics of information to market participants.[15] Instead, we allowed buyers and sellers to infer them from historical data. The finding that prices initially did not differ much between conditions but then diverged over time and stabilized at a relatively constant level indicates that the market was able to "learn" the implications of quality differences. Other elements of our experimental market could have worked against us. For example, the price of the third set of forecasts provided the same anchor for both quality conditions. In addition, buying multiple forecasts was at odds with the MARKSTRAT simulation, in which all other market research was available only from a single seller. Indeed, the experiment shows that both buyers and sellers made remarkably good qualitative assessments about the characteristics of information products and their value. This finding is notable when contrasted with previous experiments on the demand side of information markets (see, e.g., Einhorn and Hogarth 1981). Although existing studies show that people are not good statisticians when it comes to optimal acquisition of information or the correct combination of multiple information sources, our study suggests that they are good strategists in the sense that they can qualitatively assess the market value of information and trade it off against its cost. Specifically, people seem to perceive the redundancy of information products when these are of high quality, and conversely, they perceive their complementarity when information is of low quality. However, their reaction to these information characteristics is not independent of the price of information.

On the demand side, our results related to purchase quantities are also notable. Here, the basic finding is that in both experimental conditions, buyers tend to purchase more than one information product. By naive interpretation, this consumer behavior contradicts normative decision theory

[15]Sarvary and Parker (1997) assume that information characteristics are common knowledge, and their model does not specify how market participants learn them.

because it appears as if participants combined information products and ignored the benefits associated with doing so. However, this interpretation is misleading and shows the importance of carefully considering the idea that prices and quantities are simultaneously established in equilibrium. Most experiments in marketing include only one type of decision maker in a market, either customers or sellers, which implicitly fixes one of these two variables. Using an experiment in which both buyers and sellers interact repeatedly over time enabled us to support the theoretical prediction about purchase quantities. In the high-quality condition, consumers' unwillingness to combine multiple products pushed prices lower because it triggered intense competition between information sellers. At low equilibrium prices, buyers ended up buying from multiple sellers. In contrast, in the low-quality condition, it pays for consumers to purchase from more than one source. Here, competition forces firms to price higher to extract the maximum surplus from consumers, thus forcing consumers to decide between not buying at all and buying multiple products. Although in the experiment several buyers bought only one report, in the low-quality condition, a much larger number of buyers decided not to buy any information at all. Thus, buyers in the low-quality conditions were much more likely to consider the purchase of either no information products or multiple information products. These results show the subtle interaction between competitive pricing and consumer behavior in information markets.

The results from our second experiment further substantiate Sarvary and Parker's (1997) theoretical predictions. The first result confirms the counterintuitive prediction that having (some) competition can be more profitable than being a monopolist. The second result is important because it shows that there is a limit to the complementarity effect of competition on information prices. In particular, it shows that the participants were able to understand the value of acquiring information from multiple sources and did not use simple decision heuristics, such as "either buy nothing or everything." Finally, showing that monopoly prices are higher than prices under strong competition provides further validity to the experimental market.[16]

Our study has a few limitations. Our experimental information market is based on MARKSTRAT, in which the environment itself develops endogenously over time on the basis of competing firms' (information buyers in our experiment) decisions. Thus, we do not have full control over the experimental market, and differences between prices could be confounded with differences between industries. This is a price that we must pay for using a more complex decision environment. We tried to address this problem by showing that including various covariates in the analysis to capture differences between MARKSTRAT industries did not change the results.[17] To address this important concern further, we also replicated the entire first experiment using a different MARKSTRAT scenario (i.e., different parameter setting to influence industry evolution), using different participants, and always having three competing information sellers (for a conservative test). The average prices in the low-quality condition were somewhat lower than we obtained in the first experiment, but the differences in prices between the high- and low-quality conditions were again statistically significant. Moreover, the average price in the low-quality condition was still higher than the price in the monopoly condition. In summary, the replication yielded results that were fully consistent with the results presented in this article.

We also assumed that the existence of strategic interactions between information buyers does not have a significant effect on the value of information. We are confident that one-period forecasts do not represent a large strategic advantage for MARKSTRAT firms. The debriefing also provides evidence that these forecasts were used for operational decisions (e.g., setting production quantities) rather than for strategic decisions (e.g., whether to enter a new market).[18] For this, teams used the qualitative growth forecast for the different segments. In addition, although Iyer and Soberman (2000) show that sellers may take into account in their selling strategies whether information provides a large strategic advantage to buyers, these selling strategies can be implemented only if buyers are allowed to sign exclusive contracts with sellers. We did not allow this to happen. Our research design made it impossible to do so. Furthermore, it was not possible for information vendors to sell information "under the table," because they never had forecasts before the MARKSTRAT decision was over. Finally, and most important, recent research (see Xiang and Sarvary 2005) shows that strategic interactions between buyers reduce complementarity between low-quality information products, indicating that our market experiment is a conservative test of the theory. Although we cannot entirely rule out the effect of these competitive externalities, it is highly unlikely that they are responsible for our empirical findings.

REFERENCES

Arora, Ashish and Andrea Fosfuri (2005), "Pricing Diagnostic Information," *Management Science*, 51 (7), 1092–1100.

Bakos, J. Yannis and Erik Brynjolfsson (1999), "Bundling Information Goods: Pricing Profits and Efficiency," *Management Science*, 45 (12), 1613–30.

——— and ——— (2000), "Bundling and Competition on the Internet," *Marketing Science*, 19 (1), 63–82.

Christen, Markus (2005), "Research Note: Cost Uncertainty Is Bliss: The Effect of Competition on the Acquisition of Cost Information for Pricing New Products," *Management Science*, 51 (4), 668–77.

Chu, Wujin and Paul R. Messinger (1997), "Information and Channel Profits," *Journal of Retailing*, 73 (4), 487–99.

Connolly, Terrry and P. Serre (1984), "Information Search in Judgment Tasks: The Effects of Unequal Cue Validity and Cost," *Organizational Behavior and Human Performance*, 34, 387–401.

[16]Although we do not make a prediction for how low prices should be in the strong competition condition, it could be argued that they should be similar to the prices in the high-quality condition. For Sonites, we find no statistically significant difference ($t = .31$, $p = .75$). However, for Vodites, the difference is statistically significant ($t = 2.31$, $p = .02$).

[17]Different industry evolution also caused the empirical distribution of the sold forecasts not to be entirely consistent with that of the historical data we provided. However, this difference was extremely small, and even if participants had perceived this, it would not have provided different incentives for buying information.

[18]Differences in prices across the two conditions also suggest that buyers purchased information more for their own decision making than to protect themselves from strategic disadvantage (in the latter case, prices should have been higher in the high-quality condition).

Deshpandé, Rohit and Gerald Zaltman (1982), "Factors Affecting the Use of Market Research Information: A Path Analysis," *Journal of Marketing Research*, 19 (February), 14–31.

——— and ——— (1984), "A Comparison of Factors Affecting Researcher and Manager Perceptions of Market Research Use," *Journal of Marketing Research*, 21 (February), 32–38.

Einhorn, Hillel J. and Robin M. Hogarth (1981), "Behavioral Decision Theory: Processes of Judgment and Choice," *Annual Review of Psychology*, 32, 53–88.

Gerstner, Eitan (1985), "Do Higher Prices Signal Higher Quality?" *Journal of Marketing Research*, 22 (May), 209–215.

Glazer, Rahsi, Joel H. Steckel, and Russell S. Winer (1989), "The Formation of Key Marketing Variable Expectations and Their Impact on Firm Performance: Some Experimental Evidence," *Marketing Science*, 8 (1), 18–34.

———, ———, and ——— (1992), "Locally Rational Decision Making: The Distracting Effect of Information on Managerial Performance," *Management Science*, 38 (2), 212–26.

Ho, Teck H., Noah Lim, and Colin F. Camerer (2006), "Modeling the Psychology of Consumer and Firm Behavior with Behavioral Economics," *Journal of Marketing Research*, 43 (August), 307–331.

Holbert, N.A. (1974), "How Managers See Market Research," *Journal of Advertising Research*, 14 (December), 41–46.

Iyer, Ganesh and David Soberman (2000), "Markets for Product Modification Information," *Marketing Science*, 19 (3), 203–226.

Jensen, Fred O. (1991), "Information Services," in *The AMA Handbook of Marketing for the Service Industries*, Chap. 22, Carole A. Congram and Margaret L. Friedman, eds. New York: AMACOM, 423–43.

Krum, J.R. (1978), "B for Marketing Research Departments," *Journal of Marketing*, 42 (October), 8–12.

Larréché, Jean-Claude and Hubert Gatignon (1998), *MARKSTRAT 3*. Cincinnati: South-Western College Publishing.

McKelvey, Richard D. and Talbot Page (1990), "Public and Private Information: An Experimental Study of Information Pooling," *Econometrica*, 58 (6), 1321–39.

Moorman, Christine, Rohit Deshpandé, and Gerald Zaltman (1993), "Factors Affecting Trust in Market Research Relationships," *Journal of Marketing*, 57 (January) 81–101.

Ofek, Elie and Miklos Sarvary (2001), "Leveraging the Customer Base: Creating Competitive Advantage Through Knowledge Management," *Management Science*, 47 (11), 1441–56.

Patterson, Paul G. (1995), "Choice Criteria in the Final Selection of a Management Consultancy Service," *Journal of Professional Services Marketing*, 11 (2), 177–87.

Raju, Jagmohan S. and Abhik Roy (2000), "Market Information and Firm Performance," *Management Science*, 46 (8), 1075–1084.

Rötheli, Tobias F. (2001), "Acquisition of Cost Information: An Experimental Study," *Journal of Economic Behavior & Organization*, 46 (2), 193–208.

Sarvary, Miklos (2002), "Temporal Differentiation and the Market for Second Opinions," *Journal of Marketing Research*, 39 (February), 129–36.

——— and Philip M. Parker (1997), "Marketing Information: A Competitive Analysis," *Marketing Science*, 16 (1), 24–38.

Schoemaker, Paul (1989), "Preferences for Information on Probabilities Versus Prizes: The Role of Risk-Taking Attitudes," *Journal of Risk and Uncertainty*, 2 (1), 37–60.

Slovic, Paul, Baruch Fischhoff, and Sarah Lichtenstein (1977), "Behavioral Decision Theory," *Annual Review of Psychology*, 28, 1–39.

Sunder, Shyam (1992), "Market for Information: Experimental Evidence," *Econometrica*, 60 (May), 667–95.

Villas-Boas, Miguel J. (1994), "Sleeping with the Enemy: Should Competitors Share the Same Advertising Agency?" *Marketing Science*, 13 (2), 190–202.

——— and Russell S. Winer (1999) "Endogeneity in Brand Choice Models," *Management Science*, 45 (10), 1324–38.

Violino, Bob and Rich Levin (1997), "Analyzing the Analysts," *Information Week*, (November 17), 38–56.

Winkler, Robert (1981), "Combining Probability Distributions from Dependent Information Sources," *Management Science*, 27 (4), 479–88.

Xiang, Yi and Miklos Sarvary (2005), "Pricing Information: The Interaction of Competitive Externality and Information Quality," working paper, INSEAD.