IMPROVING MARKETING FORECASTING THROUGH COLLECTIVE MARKET INTELLIGENCE

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ABSTRACT

New product development and management are critical to the long-term success of the firm. New product development is also an area where the firm needs to improve performance. Two important new product decisions are selecting new concepts and estimating their future market potential and demand. Forecasting is a critical activity in supporting these two decisions. Unfortunately, forecasting is an activity where firms often struggle to be proficient. Recent advances in forecasting methods offer opportunities for improvement. One of the techniques is prediction markets, an emerging methodology that taps collective intelligence. Despite widely reported application and promise of prediction markets, they have yet to be adopted in marketing practice or examined in marketing academia. This dissertation addresses two research questions: do prediction markets produce better marketing forecasts than methods traditionally employed by firms, and if they do, how do they do it? To answer these research questions, two field studies are completed. The first is an empirical test of prediction markets compared to traditional forecasting methods implemented within a Fortune 100 firm. The second, based on a post survey, is an analysis of how market knowledge factors in combination with prediction markets design factors produce superior results. Study I finds that prediction markets do provide superior results in 67% of the forecasts and reduce error levels and ranges. Study II finds that out of several design factors, prediction market forecast accuracy is driven most by new information acquisition and knowledge heterogeneity. These findings contribute to MSI 2012-2014 Research

Priorities and calls in the marketing literature to develop, better, real-time, intelligent decision support tools to help solve problems of the big data era and support improved demand forecasting.

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Thank you.

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CHAPTER 1

INTRODUCTION

New product development and management are critical to the long-term success of the firm. Not only do new ventures fuel sales growth for many firms, but they also serve as sustainable forms of competitive advantage (Cooper 1984; Mahajan and Wind 1988; Calantone and Di Benedetto 1988; Brown and Eisenhardt 1995). As dynamic capabilities of the firm new product development, market learning, and strategic decision-making, together play an important role in the firm responding to a changing marketplace. New product development is also an area where the firm needs to improve performance (Christensen, Cook, and Hall 2005; Cooper and Kleinschmidt 1987; Barczak 2009). Review of the new product and marketing capabilities literature suggests that market learning and strategic decision-making need to change in order to improve firm performance in new products and overall (Marsh and Stock 2006; Winter 2003; Day 2011). Two important decisions in the new products process are selecting the best new concepts and estimating their future market potential and demand (Kahn et al. 2012; Thomas 1987; Hardie, Fader, and Wisniewski 1998; Mahajan and Wind 1988). This also applies to new services, markets, channels, and promotions. Marketing plays a lead role in making and influencing these decisions as they are uniquely suited to facilitate the creation and promotion of new ventures (Verhoef and Leeflang 2009; Kahn 2002).

In developing and launching new products and programs, forecasting is a critical activity (Fildes and Hastings 1994; Cohen, Eliashberg, and Ho 1997). Forecasting is necessary to know which ventures to pursue and what their business impact will be. Forecasting is highly related to three drivers of new product success: the use of market knowledge, improved decision making, and effective launch practices. Marketing forecasts use market knowledge and serve as a key input into decision making. Unfortunately, forecasting is an activity where firms often struggle to be proficient. In spite of the availability of sophisticated systems and support, effective sales forecasting is an area where companies need to improve (Mahajan and Wind 1992). Flawed analysis, high error rates, and poor decisions frequently result in massive amounts of wasted human effort and money (Kahn 2002). This hurts a company's growth potential, profitability, and competitiveness. A recent example of this issue is P&G's failed launch of their new Tide Pods product. Due largely to a failure in demand forecasting, P&G had to restrict shipping of promotional merchandise severely compromising the launch of this product. Worse is the potential loss of competitive advantage as competitors enter and gain market share in an area P&G stated is the biggest laundry innovation in decades (Neff 2012a; Neff 2012b). This is not the first time P&G encountered such a set back; in 2010 a similar issue occurred with the launch of Fusion Pro Glide razors. This issue is also raised in the new product literature (Di Benedetto 1999; Fildes and Hastings 1994). P&G's CEO states they are looking towards investments and improvements in digital tools to support forecasting and innovation (Neff 2012b). This raises the question, how can new product forecasting be improved to better support new product success for the firm?

Advances put forth in the forecasting literature offer marketing an opportunity to improve analytics and forecasting by exploiting new innovative techniques (Armstrong

2006). One of the techniques is prediction markets, an emerging form of collective intelligence, being tested and validated in other research domains and business functions. Prediction markets offer marketing the opportunity to have a higher success rate at picking winning product and promotional concepts and forecasting their sales impact. They have a track record of predicting future outcomes with better accuracy than traditional methods with more accurate point estimates and reduced variance (Hopman 2007; Ho and Chen 2007). Review of the prediction markets literature describes them as an application of collective intelligence based on several design characteristics that collect and combine information in a unique way and produce predictions and information directly suited to decision making (Page 2007). In the *Wisdom of Crowds*, Surowiecki (2005) observes that “under the right circumstances, groups are remarkably intelligent, and are often smarter than the smartest people in them” (p. xiii) and “when our imperfect judgments are aggregated in the right way, our collective intelligence is often excellent” (p. xiv). Collective intelligence applications use central technology platforms to collect and integrate information from multiple participants to predict uncertain future outcomes, solve problems, or design solutions. The rationale is if many diverse people are able and willing to share new information and different opinions, and their opinions are aggregated, then the quality of information and decisions may be improved. Thomas Malone, director of MIT’s Center for Collective Intelligence defines collective intelligence as “groups of individuals doing things collectively that seem intelligent” (Malone 2006). The Center’s key research question and mission is, “How can people and computers be connected so that collectively they act more intelligently than any individual, group, or computer has ever done before?” Preliminary evidence indicates that collective intelligence applications, such as prediction markets, may contribute to improved forecasting and decision making (Van Bruggen et al. 2010; Spann and Skiera 2003).

Despite the widely reported application and promise of prediction markets from several other disciplines, they have yet to be adopted in marketing practice or examined in marketing academia. Before they can be considered as a new methodology, however, their efficacy must be demonstrated in marketing and their mechanism explained (Armstrong 2006). Surowiecki (2005) shares an observation from an economist that highlights this need, "While markets appear to work in practice, we are not sure how they work in theory" (p. 9). The design factors of collective intelligence and prediction markets have been introduced in various disciplines and literatures, but their effects have not been formally explained or empirically tested. This leads to the two research questions for this dissertation: do prediction markets produce better marketing forecasts than methods traditionally employed by firms, and if they do, how do they do it?

Theory on market knowledge creation and use provides a useful established framework for studying where and how prediction markets may contribute to learning and decision making improvements. The framework consists of market information processing (information acquisition, interpretation, and dissemination) and its outcome market intelligence (organizational memory) that support marketing decisions (Sinkula 1994; Moorman 1995; Sinkula, Baker, and Noordewier 1997). This dissertation proposes that prediction markets are a tool that can employ market knowledge to produce more accurate forecasts that can support improved marketing decisions in new product development and other important areas. The objectives of this dissertation are i) to develop an understanding of prediction markets and their application to marketing, ii) to empirically test whether they can improve marketing forecasting outcomes and, if they can, iii) to examine how they produce superior accuracy results. To answer these research questions, two field studies were completed.

In the first study, an internal prediction market was designed and implemented as an academic-practitioner collaboration with a Marketing Science Institute (MSI) member company and a leading collective intelligence consulting firm. A fully functional prediction market generated 22 marketing forecasts, across three autonomous operating divisions, for a specific future fiscal time period. Approximately 200 internal corporate employees participated in the prediction market over an eight week period. The same three categories of forecasts were compared across each of the three operating divisions: new product sales, supply chain shipments, and overall division dollar sales. The first field study tests whether prediction markets actually improve forecasting outcomes for real marketing problems. Prediction market forecasts are compared to company internal forecasts, relative to actual outcomes, to assess prediction markets' potential to improve marketing forecasting and decision making. Study I's comparison finds that prediction markets provide superior results in 67% of the forecasts, reduce average error, and reduce the error range.

The second field study attempts to explain the apparent mechanism of prediction markets. A cross sectional post survey of 103 prediction market participants gathered data to examine the effects of prediction market design factors on forecast accuracy. In the conceptual framework, market knowledge factors of information acquisition, interpretation, and dissemination are combined with prediction market factors of knowledge heterogeneity, independence, and incentives. Considering the market knowledge factors as behavioral factors and the prediction market factors as organizational/cultural provides a perspective that helps explain their role and impact (Kirca, Jayachandran, and Bearden 2005; Day 1994; Bharadwaj, Nevin, and Wallman 2012). PLS-SEM analysis finds that information acquisition and knowledge heterogeneity are the drivers of prediction markets' improved accuracy. The results suggest that prediction markets offer the most benefit in situations where information and insights are less available and developed. Benefits are shown here for cases that are more continuous or dynamically continuous types of innovation. There may be even greater potential for more radical or discontinuous innovation where information is typically less available (Anderson and Ortinau 1988; Garcia and Calantone 2002). The results also introduce a new information element particularly useful when forecasts need to be accompanied by an assessment of uncertainty or risk such as with marketing investment decisions (Rao and Bharadwaj 2008). In addition to their point estimates, prediction market outputs provide probability distributions of estimates.

Contributions of this research are made to prediction markets theory by providing needed field tests and validation with realistic business problems and other business areas; to forecasting theory by providing a new formal method from other disciplines to combine forecasts and support key decisions in marketing; to new products by providing a way to screen early new concepts and estimate demand at launch; to decision making by providing a decision support tool that integrates market knowledge into decision ready information; and to market knowledge by showing how marketing information processing can be enhanced to provide task specific intelligence. Specifically, this research responds to MSI 2012-2014 Research Priorities by introducing a method from other disciplines to help solve problems of the big data era; developing, a better, real-time, intelligent system and decision support system; and supporting improved demand forecasting.

In order to better understand how prediction markets may improve new product forecasting, they should be examined within the context of new products, the interrelated capabilities of market knowledge and decision-making, and forecasting. To achieve this, chapter two reviews the major findings, drivers, issues, and questions in the new products, capabilities, market knowledge, marketing decision making, forecasting, and prediction markets literatures. Chapter three develops a theoretical framework and proposes seven hypotheses to address the research questions. Chapters four and five present the methodologies and results of two field tests. Chapter six is a discussion of the results, their contributions to the marketing theory and practice, limitations, and areas for future research.

The design and implementation of the field studies have been financially supported by a Temple University CIBER Grant ($10,000), a grant from the subject company ($35,000), a grant from the consultant-service provider Lumenogic ($40,000 in kind services), and a grant from Saint Joseph's University C.J. McNutt Chair of Food Marketing ($3,400).

CHAPTER 2

LITERATURE REVIEW

New Product Development

New product forecasting is the focal subject of this dissertation, so the new product development literature provides a necessary context. New product development is critical to the success of the firm. There are two common themes regarding the importance of new products: their strategic value to the firm and their contribution to revenues and profits and their future growth. The strategic value to the firm is described in terms of new product development being a key element of corporate strategy (Cooper 1984), defending or maintaining market share (Mahajan and Wind 1988), and gaining and keeping a strong competitive position or advantage (Calantone and Di Benedetto 1988; Brown and Eisenhardt 1995). Brown and Eisenhardt (1995) state that "product development is among the essential processes for success, survival, and renewal of organizations, particularly for firms in either fast-paced or competitive markets" (p. 344). Observations on revenues and profits include new products' contribution to growth and prosperity (Cooper and Kleinschmidt 1987), profitability (Calantone and Di Benedetto 1988), and significant portions of sales (Di Benedetto (1999).

New product development and management need to improve. Assessments of the new product process by researchers and practitioners have often been critical of the low success rate.

Although product commercialization failure rates often are reported to be as high as 90% (Christensen et al. 2005), the overall failure rates for goods and services is closer to 40% (Crawford and Di Benedetto 2011; Cooper and Kleinschmidt 1987; Barczak 2009).

One common reason cited is the poor performance of the new product development process. Wind and Mahajan (1997) observe that advances in new products research, development, and marketing knowledge and processes have not lead to acceptable new product success rates. Di Benedetto (1999) finds that product launch is not performed effectively by many firms. Christensen et al. (2005) find the high failure rate is despite massive amounts of spending trying to understand what consumers want. All of these authors reinforce improvements are needed. To better understand how new product development might improve, its drivers and issues and their impact on performance should be examined in detail. Table 1 summarizes seven prominent articles that examine the new product development process over the past 28 years. For each article, independent and dependent variables, analysis method, key findings, and future research questions are identified.

In the sections that follow, information from these and other articles is used to review predictors of new product performance, areas of needed improvement, areas of further study, and implications for the study of new product forecasting.

Table 1. New Product Development Literature Review Table

Source	"An Examination of New Product Development Best Practice," Kahn et al. 2012	"Issues and Opportunities in New Product Development: An Introduction to the Special Issue," Wind and Mahajan1997
Purpose Research Question	Examine dimensions of new product development (NPD) best practice, their importance, and the state and degree of application in practice.	Identify issues and suggestions to increase efficiency and effectiveness of new product development (NPD) and innovation activities.
Theoretical Elements	Importance of NPD dimensions (DV) Strategy Research Commercialization Process Company culture Project climate Metrics Maturity of dimensions in practice	The outputs of the NPD process (2 items) The context of NPD (5 items) The scope of NPD (5 items) The process of NPD (6 items)
Analysis	Two phase study of exploratory Delphi to develop constructs and a survey to measure importance and maturity. 306 industry practitioners across the U.S. and UK drawn from executive education and association members. Analysis includes frequency distributions, significance tests, and mutlidemensional scaling.	Review of articles in special issue supplemented with review of new product development research and practice overall.
Key Findings	The most important dimensions are strategy, research, and commercialization. Managers lack understanding of best practice elements of climate, culture, and metrics. It is important that managers articulate a clear new product strategy and consider the fit of their projects.	In spite of a rapidly changing marketplace, new product development research and practice have not advanced significantly. A drastic rethinking and retooling of new product development research and practice is needed to cope with changing marketplace.
Future Research	Research needs to continue to identify what best practice really means for new product development and how companies can achieve these practices.	Challenge the marketing community to develop new research and modeling approaches capable of dealing with new problems and new solutions and discontinuous innovations under uncertain market conditions.

Table 1. (continued)

Source	"Product Development: Past Research, Present Findings, and Future Directions," Brown and Eisenhardt 1995	An Integrative Model of the New Product Development Process: An Empirical Evaluation," Calantone and di Benedetto 1988
Purpose Research Question	Identify and organize key dimensions and drivers of new product success and develop future research agenda.	Demonstrate the inter relationships that exist between established determinants of new product success and their impact on outcomes.
Theoretical Elements	Financial performance (DV) Process performance Market attractiveness Product concept effectiveness Team composition Team group processes Organization of work Customer and supplier involvement Senior management involvement Project leadership	Product profit (DV) Product success or failure (DV) Technical resources, skills and activities Marketing resources, skills and activities Market intelligence activities Launch activities Relative product quality
Analysis	Review of empirical literature from 1969-1995 with the development project as unit of analysis. Identify and synthesize key dimensions and drivers of new product success into a single model.	Surveys mailed to 300 U.S. firms published in registers plus snowball sample produced 189 completed surveys. Survey was abridged version of Cooper Newprod. Scaled key informant assessments of new product development process and outcomes. Factors analyzed through a system of equations using 3stage least squares.
Key Findings	New product success influenced by three dimensions: i) careful plan, superior product, attractive market, effective execution, support of senior management ii) new and varied information, internal/external communications iii) speed, flexibility, autonomous problem solving with strong leaders.	Overall R-Sq for model was 0.312. All proposed relationships but one were supported at the $p<0.05$ level. Marketing and technical resources, Marketing and technical activities, and Market and technical intelligence affect product success. Launch activities not related to product success.
Future Research	Use advanced methods to examine the relationships between factors, the factors and performance and themselves and importance of factors. Study the organization of work regarding highly structured disciplined vs. flexible fluid models. Study the changing roles and effects of management and leadership of the new product development process.	Study focused on industrial products, consumer products should also be examined. Advances in key factor and outcome measures. Further analysis of the role of launch activities would also be beneficial to overall understanding.

Table 1. (continued)

Source	"Why Some New Products Are More Successful Than Others ," Henard and Szymanski 2001	"New Products: What Separates Winners from Losers?" Cooper and Kleinschmidt 1987
Purpose Research Question	Meta-analysis of empirical evidence on the determinants of new product performance.	Develop a model of new product success and failure and test the impact of key factors on new product outcomes.
Theoretical Elements	New product performance (DV) Product characteristics (5 items) Strategy characteristics (5 items) Process characteristics (11 items) Marketplace characteristics (3 items) Measurement moderators (4 items) Context moderators (3 items)	New product success (DV) (11 items) Product advantage (6 items) Market potential (4 items) Market competitiveness (6 items) Marketing synergy (5 items) Technological synergy (3 items) Protocol (4 items) Prof. of predevelopment activities (5 items) Prof. of market-related activities (5 items) Prof. of technological activities (5 items) Top management support (3 items)
Analysis	Mean correlation analysis of 24 factors across 41 studies. Multiple regression of performance onto factors. ANOVA analysis of differences in performance across moderators.	Sample of 203 projects from a listing of manufacturing firms. Personal interviews with managers based on questionnaire. Ten constructs measured through validated multi-item scales. Correlations between factors and success combined with ANOVA analysis between successful and failed projects.
Key Findings	Ten factors found to have significant impact on performance including product advantage, market potential, meeting customer needs, predevelopment task proficiencies, and dedicated resources. Varied effects of moderators on relationships with performance.	Of the ten hypothesized factors, nine significantly related to new product success: product advantage, proficiency of predevelopment activities, and protocol exhibited particularly strong impacts. These are variables largely in the control of management.
Future Research	Further testing with more objective and multi-item measures. Further study of how firms generate and screen new ideas. Testing inter relationships amongst the predictors is needed.	The use of bivariate correlations in this study is a weakness that could be overcome today with SEM. Many of the scales look to be formative but are tested as if they were reflective. The need for a more complete test of the model is indicated which could address both of these weaknesses.

Table 1. (continued)

Source	"How New Product Strategies Impact on Performance," Cooper 1984
Purpose Research Question	Examine the relationship between new product performance and new product strategies.
Theoretical Elements	Three dimensions of performance: impact, success rate, and relative performance (DVs) 19 strategy dimensions hypothesized to influence performance. Dimensions fall into four categories: nature of products developed, nature of markets sought, nature of technology employed, and orientation and nature of the new product process.
Analysis	Surveys mailed to Canadian industrial firms known to be active in new product development, with 122 completed responses. Manager assessments of 66 scaled strategy variables. Factor, validity, and reliability analysis reduced set to 19 strategy dimensions. Relationships analyzed through regression analysis of three performance outcomes against factors plus canonical correlations between same.
Key Findings	Different performance dimensions are achieved by different combinations of strategy dimensions. Few if any firms can achieve high performance across all three dimensions simultaneously. There are three tendencies: a high impact risky program with aggressive strategies, a high success rate safe program with conservative strategies, and a high relative performance program with a balance of strategies.
Future Research	The surprising negative impact of marketing synergy could be explored further to better understand this effect. The non-significance of competitive factors could be explored further to better understand their lack of effect. Testing inter relationships amongst the factors is needed.

Cooper (1984) defines three dimensions of performance: business impact, which describes impact on company sales and profits; success rate, which gauges track record in terms of success and kill rates; and relative performance, which captures the overall performance of the program relative to objectives and competitors, and in terms of profits versus costs.

Predictors of New Product Performance

Table 2 compiles the predictors of new product performance from several prominent review studies in the new products literature. Thirty six factors identified from these studies are organized by six common categories: firm strategy, firm resources and capabilities, product characteristics, development process, team and organization, and marketplace. Table 2 indicates the study that examined each factor and the number of times they were examined. The columns label the studies as A - G and the number of times they were examined as '#'. The authors are identified below the table.
From Table 2, ten of the 36 factors were identified three to five times across the studies suggesting that they are the most prominent factors. Note there are prominent factors from each of the six categories. In addition to prominence, Table 2 also indicates factor importance. Factors found to have a significant relationship with performance or success in their study are marked with an asterisk and those that were not found significant or that were not empirically tested are marked with an 'x'. Depending on the study, a significant relationship with performance or success could pertain to differences between successful/failed groups, correlation with outcomes, regression coefficients, or stated

importance. Fourteen factors are identified in more than one study as having a significant relationship with new product success. This multi-study corroboration suggests that the following fourteen factors are the most important drivers of new product success: firm strategy (marketing synergy/fit, technological synergy/fit, strategy); firm resources and capabilities (competitive & market intelligence, company resources/spending, technical/R&D resources & skills, dedicated human resources); product characteristics (product advantage); development process (prof. technical activities, prof. marketing activities, prof. pre-develop activities, process/protocol, launch/commercialization activities); and marketplace (market potential/attractiveness).

Reviewing the drivers of new product success across the literatures, three high level areas are repeated that are directly related to the issue of improved new product forecasting: market knowledge, decision making, and launch activities. The link between these factors made in this dissertation is that market knowledge is used to make forecasts which then serve as inputs to decisions regarding selecting new product concepts and forecasting market demand for launch preparation. For example, Calantone and Di Benedetto (1988) identify market intelligence, decision making, and launch activities as three of several key determinants of new product success. They describe how market intelligence can be used by the firm to make better marketing decisions. As they discuss the new product development model adapted from Cooper (1980), they make an important distinction between technical and market activities that complement each other at each stage of the new product development process.

Table. 2 Predictors of New Product Performance

Factors-Predictors	A 1984	B 1987	C 1988	D 1994	E 1995	F 2001	G 2012	#
Firm Strategy:								
Marketing synergy/fit	x	*		*		x		4
Technological synergy/fit	x	*		*		x		4
New product strategy	x			*			*	3
Product fit with firm competencies	x				x			2
Order of entry						*		1
Market orientation/fit						x		1
Firm Resources & Capabilities:								
Competitive & market intelligence			*	*		x	*	4
Company resources/spending	x			*			*	3
Technical/R&D resources & skills			*			*		2
Dedicated human resources						*	*	2
Marketing resources & skills			*					1
Product Characteristics:								
Product advantage	x	*		*		*		4
Product meets customer needs					x	*		2
Product innovativeness/tech. soph.	x					*		2
Product quality			*					1
Product price						x		1
Development Process:								
Prof. technical activities	x	*	*	*		*		5
Prof. marketing activities		*	*	*		*	*	5
Prof. pre-develop activities		*		*		*	x	4
Process/Protocol		*		*			x	3
Speed to market				*	x	x		3
Launch/commercialization activities			x			*	*	3
Structured/planned approach					x	x		2
Flexibility/Overlapping processes					x		x	2
Financial/business/cost analysis				*				1
Productivity					x			1
Metrics/performance measurement							x	1

Table 2. (continued)

Factors-Predictors	A 1984	B 1987	C 1988	D 1994	E 1995	F 2001	G 2012	#
Team & Organization:								
Top management support/skill		x		*	x	x		4
Internal/external relations and culture				*	x		x	3
Cross-functional integration					x	x	x	3
Customer/supplier involvement					x		x	2
Effective project leadership					x		x	2
Cross-functional communication						x		1
Sufficient team tenure					x			1
Marketplace:								
Market potential/attractiveness	x	*		*	x	*		5
Competitiveness/intensity	x	x		*		x		4

A Cooper 1984
B Cooper & Kleinschmidt 1987
C Calantone & Di Benedetto 1988
D Montoya-Weiss & Calantone 1994
E Brown & Eisenhardt 1995
F Henard & Szymanski 2001
G Kahn et al. 2012

Number of studies examining factor

* Found significant in analysis

x Not analyzed or not found significant

The marketing activities include selecting concepts based on customer needs and a series of analyses that would include various forms of forecasts: early forecasts would be related to assessing market potential and later forecasts would be related to market demand supporting commercialization. In their description Calantone and Di Benedetto (1988) state, “At each stage in the process, information is gathered, assessed and evaluated, and finally decisions on whether to continue with the project are made… the nature of the commercial entity will depend upon (1) the nature of the activities undertaken by the firm, (2) the quality of the marketing and technical information obtained, and (3) how well the decisions were made” (p. 206). In this same vein, Cooper and Kleinschmidt (1987) identify product launch, information, and decision making, as part of the several factors in their model of new product success. They also mention the importance of effective screening and selection of projects and the need for financial evaluation. Kahn et al. (2012) identify the importance of determining market size and potential and expected sales revenues. Regarding market knowledge, Marsh and Stock (2006) link the ability to integrate market knowledge into the new product development process as a key success factor; Brown and Eisenhardt (1995) describe how communication based on information-processing brings new and varied information into the new product development process; and Kim and Atuahene-Gima (2010) emphasize the relationship between market information processing, and market learning, and new product performance. Regarding decision making, Calantone and Di Benedetto (1988) identify two of the important factors leading to product success as market intelligence and decision making; Krishnan and Ulrich (2001) explain that product development is a process involving scores of generic decisions; and Brown and Eisenhardt (1995) characterize the new product development process as problem-solving process involving many decision-making activities. Finally, the importance of launch practices and commercialization is identified in numerous studies (Di Benedetto 1999; Kahn et al. 2012; Calantone and Di Benedetto 1988).

New product forecasting is examined specifically in the new products and forecasting literatures. For example, Mahajan and Wind (1992) identify analytical aspects of new product development that are related to forecasting activities including new product concept screening, detailed market study, business/financial analysis, pre-market volume prototype forecasting, and market launch planning. Surprisingly, they find that formal models and tools are used most infrequently for pre-market volume forecasting, business/financial analysis and market launch planning. Calantone and Di Benedetto (1988), identify marketing activities that must be done well including rough sales projections to determine future market potential. Cohen, Eliashberg, and Ho (1997) discuss how decision support systems can improve the new product development process as tools to integrate data and model key decision outcomes such as multi-stage forecasts. Forecasts are described as critical inputs to decisions as products move through the new product development process.

An important distinction is made in the new products literature regarding the degree of innovativeness of new products. The literature frames this continuum (from high to low) as radical, really new, discontinuous, disruptive, incremental, and imitative innovation (Garcia and Calantone 2002; Cooper 2000). The main question is how different are new products from a firm's core business and what are the implications for the process, information, and decisions. For example, Garcia and Calantone (2002) find that "Market learning for really new innovations differ drastically from those associated with conventional new product development processes" (p. 126). The acquisition, flow/sharing, and use of new information for new products with higher degrees of innovativeness are specifically studied, especially the challenges of the early stages (Brentani and Reid 2011) and improved prediction capabilities (Anderson and Ortinau 1988). Researchers are challenged to understand how high versus low innovativeness development processes are different from each other and how to support them (Garcia and Calantone 2002).

In addition to drivers of new product performance, the literature identifies several specific areas where improvements are needed. In most of the articles reviewed, forecasting is specifically identified as an area of needed improvement. In the latest PDMA best practices study, Barczak (2009) identifies idea management, project leadership and training, cross-functional training and team communication support, and innovation support and leadership by senior management. Mahajan and Wind (1992) identify major areas of improvement as more formal and quantitative approaches, enhanced use of new product models, better top management involvement, and adding better forecasting models to key activities (concept screening, market studies, and business/financial analysis). Specifically, Mahajan and Wind find forecasting inaccuracy to be the greatest area of concern regarding models and methods among practitioners they surveyed. Cooper (1984) identifies the need for a greater market orientation, more market research, better project evaluation techniques, and more attention to the market launch phase. Cooper and Kleinschmidt (1987) prioritize initial screening, preliminary technical and market assessments, marketing research, and business/financial analysis. Several areas of future needed research related to forecasting are called for in the new products literature. Di Benedetto (1999) finds that logistics and inventory strategy have not been sufficiently researched in spite of their importance, including “the ability to handle uncertainties in new product demand” (p. 532). Wind and Mahajan (1997) indicate that new approaches should be developed that leverage the power of information technology to quickly assess new product concepts within a few days rather than months. They also identify the need for new processes to utilize marketing research as part of decision support systems, decision tools, and decision-making processes including forecasting for new products and services. Marsh and Stock (2006) discuss “the need to integrate knowledge more rapidly and effectively within projects. These approaches do not address, however, how knowledge is integrated over time or how integration of knowledge from previous new product development efforts influences the firm's new product development performance" (p. 423).

The background and definition of market knowledge, decision making, and launch activities and their relationship to improved new product forecasting are expanded upon and examined further in sections that follow. New product development as a dynamic capability is also reviewed in the next section to understand further what drives its success as a dynamic capability, its relationship with market knowledge, decision making, and forecasting how it might be improved.

Firm Capabilities

New product development, market learning, and strategic decision making are described in the literature as dynamic capabilities of the firm (Marsh and Stock 2006; Winter 2003). An understanding of theory behind dynamic capabilities and how this is changing can provide useful context for how forecasting may need to change in order to better support new product development. Table 3 summarizes six prominent articles that examine the firm capabilities over the past 25 years. For each article, independent and dependent variables, analysis method, key findings, and future research questions are identified. In the sections that follow, information from these and other articles is used to review the evolution of capabilities thinking, key dimensions, areas of needed improvement, areas of further study, and implications for the study of new product forecasting.

The study of capabilities has its origins the in theories of core capabilities or resources from the resource based view (RBV). RBV conceptualizes firms as heterogeneously distributed bundles of resources that persist over time. Competitive advantage stems from resources that are valuable, rare, inimitable, and non-substitutable (Barney 1991; Eisenhardt and Martin 2000). Resources are defined as physical, human, and organizational assets that can be used to implement value-creating strategies (Eisenhardt and Martin 2000). Leonard-Barton (1992) refers to these resource bundles as core capabilities and focuses on their value as a system of embedded knowledge sets that provide competitive advantage. In a similar manner, Winter (2003) refers to ordinary or zero-level capabilities as those that permit a firm to 'make a living' in the short term.

A common observation made about resources or core capabilities is that they become deficient at providing sustained competitive advantage as the competitive marketplace changes over time. Eisenhardt and Martin (2000) consider high-velocity markets a boundary condition for the RBV focus on leveraging bundled resources to achieve long-term competitive advantage.

Table 3. Capabilities Literature Review Table

Source	"Dynamic Capabilities: What Are They?" Eisenhardt and Martin 2000	"Dynamic Capabilities and Strategic Management," Teece, Pisano, and Shuen 1997
Purpose Research Question	Explore and extend understanding of dynamic capabilities in order to enhance and clarify understanding of RBV.	Introduce a new theory of how firms build competitive advantage within rapidly changing markets.
Theoretical Elements	Resource-based view (RBV) Dynamic capabilities (DC) Market dynamism Evolution	Competitive forces Strategic conflict Resource-based perspective Dynamic capabilities Exploitation of market power Resource efficiency Processes, positions, paths
Analysis	Literature review and conceptual analysis of DCs with respect to market dynamism to reframe the definition and understanding of DCs and RBV concepts.	Literature review and conceptual analysis of three prevalent theories of source of competitive advantage and introduction of dynamic capabilities as alternative theory. Compare and contrast DCs to other established models of strategy.
Key Findings	DCs integrate, reconfigure, and gain/release resources to achieve competitive advantage. New product development, strategic decision making, and knowledge creation are prominent DCs. The role and evolution of DCs vary by moderate vs. high market dynamism and by detailed and routine to simple and experiential routines. DCs are not themselves a competitive advantage, but a way to reconfigure resources to ultimately maintain or achieve competitive advantage.	Three prevailing theories of strategy are missing a dynamic perspective on resource advantage. Dynamic capabilities suggest that competitive advantage requires both the exploitation of existing internal and external firm capabilities, plus developing new ones in response to market changes. The effect of dynamic capabilities on competitive advantage operates through firm processes, asset positions, and path dependencies.
Implications / Future Research	How can knowledge creation and application and decision making be enhanced to support the experiential form of DCs needed for high-velocity markets? What tools and processes are needed to support the frequent prototyping, real-time information, and experimentation cited?	Empirical research needed to understand how dynamic capabilities operate within firms. Joint research needed between strategy and fields such as innovation is needed.

Table 3. (continued)

Source	“Core Capabilities and Core Rigidities: A Paradox in Managing New Product Development,” Leonard-Barton 1992	Exploration and Exploitation in Organizational Learning,” March 1991
Purpose Research Question	Examination of how core capabilities can both enable and inhibit new product development.	Examine the relationship between exploration and exploitation in organizational learning.
Theoretical Elements	Core capabilities Employee knowledge and skills Technical systems Managerial systems Values and norms Core rigidities	Exploration of new possibilities Exploitation of current certainties Social context of learning Adaptive systems and processes Mutual learning Competition for primacy Knowledge heterogeneity
Analysis	Observational case studies of 20 development projects and teams in five firms. Paired comparison of two new product projects (highly congruent and non-congruent), against a core firm capability, along the four dimensions of core capabilities.	Conceptual comparison and contrast of two models of knowledge development and use in organizations. Concept of adaptive processes used as context to examine exploration and exploitation tradeoffs and returns within organizations.
Key Findings	Core capabilities provide influence and support to new products. They can also severely inhibit new products (core rigidities) when responding to environment is not aligned with them. Support or hindrance depends upon a number of dimensions in alignment or conflict with capabilities or rigidities. Changes in capabilities result from experiences with core capabilities or rigidities over time.	Differences in the risks and rewards of exploration and exploitation have adaptive processes favor the immediacy of exploitation. From the mutual learning model, new diverse individuals increase knowledge exploration, introduce new information, and improve the aggregate knowledge level of the organization. This effect is amplified when there is environmental turbulence. From the mutual competition for primacy model, the average return from knowledge increases also depends on variability and number of competitors. Knowledge and performance variance (innovation) is positively related to achieving primacy and negatively related to reliability of relative performance.
Implications / Future Research	What is the mechanism through which core capabilities change in response to interaction with new product development projects? How are the technical systems that are the processes of knowledge creation and control changing and how do they need to change to facilitate the change in capabilities?	What are the mechanisms for aggregating knowledge of diverse individuals in the explorative mode?

Table 3. (continued)

Source	"The Antecedents, Consequences, and Mediating Role of Organizational Ambidexterity," Gibson and Birkinshaw 2004	"Closing the Marketing Capabilities Gap," Day 2011
Purpose Research Question	Empirical examination of the antecedents and consequences of the introduced concept of contextual ambidexterity.	Examine the gap between the demands of the changing environment and most marketing organizations' capacity to respond. Recommend actions to address this capability gap.
Theoretical Elements	Performance (DV) Organizational context (performance management and social) Alignment and adaptability Ambidexterity Contextual ambidexterity	Information processing Decision making Static (RBV) capabilities Dynamic capabilities Adaptive capabilities Market learning capability Inside-out vs. outside-in orientation Exploitation vs. exploration Adaptive experimentation Open marketing
Analysis	A total 4,195 interviews from a random sample of executives across 41 business units of ten firms. Multi-item scales pretested for validity and reliability. OLS regression analysis supported by post hoc ANOVA and qualitative analysis.	Conceptual review and analysis of the literature, introduction of new constructs and relationships, and identification of actions to address issue.
Key Findings	Conflicting demands of alignment and adaptability require tradeoffs to maintain long-term competitiveness in changing environments. In contrast to dual structures, contextual ambidexterity, as a meta-level capacity, allows alignment and adaptability activities to work simultaneously by enabling all levels of actors to concentrate on both. Three hypotheses supported: positive relations between ambidexterity-performance, context-ambidexterity, and ambidexterity mediates context-performance relationship.	Firms need to sense weak market signals to anticipate trends and events before they are fully apparent and be more willing to experiment to respond effectively. Can be achieved by shifting from inside-out to outside-in and from exploitive to explorative orientations. Adaptive marketing capabilities require a firm to proactively sense and respond to incomplete information, learn through trial and error experimentation, and leverage a broader network of marketing partners.
Implications / Future Research	Explore additional ways to assess contextual ambidexterity and performance. Further investigate influential organizational contexts. What are tools and systems that can support contextual ambidexterity?	What new marketing capabilities will be needed? How will they help make the entire organization more adaptive? How can useful market insights be rapidly extracted?

Leonard-Barton (1992) describes embedded resources or core capabilities as core rigidities that hinder the progress of new product development projects when they are unchanging. This issue sets up discussion of the need for capabilities to change or evolve over time in response changing environments (Leonard-Barton 1992; Eisenhardt and Martin 2000). Teece, Pisano, and Shuen (1997) refer to the change or evolution of capabilities over time as dynamic capabilities. They introduce dynamic capabilities theory based on their assessment that the three prevailing theories of strategy (competitive forces, strategic conflict, resource-based perspective) missed a dynamic perspective on resource advantage; they find that competitive advantage requires both the exploitation of existing capabilities and the development of new ones in response to market changes. Teece et al. (1997) define dynamic capabilities as follows:

> The firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. Dynamic capabilities thus reflect an organization's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions…The term 'dynamic' refers to the capacity to renew competences so as to achieve congruence with the changing business environment…The term 'capabilities' emphasizes the key role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences to match the requirements of a changing environment. (p.516)

Eisenhardt and Martin (2000) offer a consistent definition of dynamic capabilities:

> Dynamic capabilities consist of specific strategic and organizational processes like product development, alliancing, and strategic decision making that create value for firms within dynamic markets by manipulating resources into new value-creating strategies…Dynamic capabilities are the antecedent organizational and strategic routines by which managers alter their resource base-acquire and shed resources, integrate them together, and recombine them-to generate new value-creating strategies. As such, they are the drivers behind the creation,

> evolution, and recombination of other resources into new sources of competitive advantage. (p. 1106)

According to Eisenhardt and Martin (2000), it is the new resource configurations that provide competitive advantage not the dynamic capabilities themselves. Winter (2003) describes dynamic capabilities as those that operate to extend, modify or create ordinary capabilities. Winter makes distinction that the cost-benefit comparison of investing in dynamic capabilities does not always make sense for firms; a simpler from of change through ad-hoc problem solving may also be an effective and economical way to respond to environmental change in certain situations.

The trade-off between exploration and exploitation is a common theme in the capabilities literature. March (1991) describes exploitation as the refinement and extension of existing competences and technologies concerned with efficient production and execution. He describes exploration as experimentation with new alternatives concerned with variation, risk taking, flexibility, and discovery. March expresses concerns that the tangibility and immediacy of the rewards of exploitation have organizations favor it over exploration; this results in organizations not seeing necessary changes and not adapting to them for long-term survival. Gibson and Birkinshaw (2004) use the terms alignment and adaptability for exploitation and exploration. They address the issue of how an organization can implement and sustain both sets of activities effectively. Rather than the traditional notion of creating different functions (dual structures) to be responsible for alignment and adaptability, they argue for creating a meta-level capacity for actors at all levels. Based on their own judgment and depending on the context of the situation or task, organizational members can practice both sets of activities. They argue that this is more sustainable in the long term and can reduce set up and coordination costs. They call this capacity to simultaneously demonstrate alignment and adaptability across an entire business unit contextual ambidexterity.

Rather than framing the discussion of the trade-offs between exploration and exploitation as discrete conditions, they can be considered as points on a continuum of capabilities change that firms undergo. This leads to an assessment of the sufficiency of the change in capabilities when faced with highly changing markets. In his argument for adaptive capabilities Day (2011) does this; he introduces and explains the need for a transition from the current dynamic depiction of capabilities to adaptive capabilities in order to respond to a growing deficiency in firms' ability to respond to the marketplace. Day argues that, because dynamic capabilities have been largely inside-out and exploitation oriented, they are not sufficient to respond to the nature and degree of changes in today's marketplace. According to Day, adaptive capabilities expand on dynamic capabilities by enabling a firm to further change, expand, or acquire capabilities based on outside-in and explorative orientations. An outside-in orientation provides a firm with heightened ability to detect shifts in the marketplace and implement necessary changes. An explorative orientation balances a firm's efficient execution focus with an openness and flexibility to experiment and learn with new opportunities presented by the marketplace. He describes how these orientations enable a firm to be adaptive, to effectively anticipate and respond to quickly changing market conditions. He also focuses on the role of marketing in making this transition. Day identifies market learning capability and market information processing as central to bridging the "marketing capabilities gap", specifically deficiencies in current information processing, prioritization, and decision making capabilities. In order to bridge the marketing capabilities gap and adapt to today's marketplace, he argues for enhanced market learning capability to sense and process new market information and to decide and act on it.

Day (2011) introduces three adaptive marketing capabilities that firms need in order to enhance their market learning capability: vigilant market learning, adaptive experimentation, and open marketing. He describes vigilant market learning as the firm's ability to sense and anticipate emerging changes in the marketplace, even if from only weak or partial signals; adaptive experimentation as the firm's willingness and ability to continuously experiment and learn based on its early reading of the market; and open marketing as the firm's ability to leverage resources dispersed throughout the firm and its network partners. The combined effect of these three capabilities is an amplified capacity for the firm to sense and respond to the many rapid and significant changes in the marketplace. In order to achieve adaptive marketing capabilities, there are significant implications for market learning capability. Day identifies several improvements to market learning capability, information processing, and decision making that will be necessary to move toward more adaptive marketing capabilities. Firms will need to expand market sensing capabilities, tap into information resources dispersed across the firm, overcome organizational impediments to learning, develop evaluation and prioritization capabilities, and improve decision making capabilities. These improvements are especially needed in the areas of innovation and new product development due to the role these play in the future growth and success of firms (Moorman 1995; Li and Calantone 1998; Day 2011). This is an important link with new product forecasting in this dissertation that has implications for the examination of and the role that prediction markets may play in improving forecasting outcomes through supporting marketing information processing.

According to Day (2011), vigilant market learning will require firms to expand their market scanning and sensing abilities in order to pick up on market changes that are occurring further out. To achieve more open marketing functions, firms will need to develop ways to tap into data, insights, expertise, and experiences dispersed across firm functions, divisions, regions, and with network partners. Valuable market information may go unused because its existence not known, it is not being shared, or it is not accessed. In order to capitalize on enhanced information gathering abilities, firms will need to overcome impediments to learning such as organizational biases and filters and shared assumptions and beliefs. These can impede how new and different market information is received, interpreted, and used. Adaptive capabilities will require not only willingness to experiment, but also the ability to sort through multiple possible opportunities and innovations. To do this, firms will need to enhance their early stage evaluation and prioritization capabilities. He identifies obstacles such as groupthink, functional silos, inertia, complacency, time lags, and path dependency. Resulting organizational influences on decision processes and general resistance to change hinder responding to new learning. Day indicates that decision processes need to be faster, more flexible and collaborative, better at sharing information, and able to work with less than perfect information. He argues that organizations have run up against limits in their ability to process massive amounts of data related to the market and new tools and approaches are needed. He calls specifically for adaptive processes that can support the kind of "just-in-time decision making" (p. 190) demanded by today's marketplace.

In addition to new product development being identified as a dynamic capability in this literature, market knowledge and decision-making are two related dynamic capabilities that are strongly related to new product development and forecasting (Marsh and Stock 2006; Winter 2003; Leonard-Barton 1992). The creation, accumulation, management, and utilization of knowledge and the tools and processes that support these activities are throughout the capabilities literature (Leonard-Barton 1992; Eisenhardt and Martin 2000; Teece, Pisano, and Shuen 1997; March 1991). And improvements to them and our understanding of them are also in the literature. For example, Day (2011) argues that a new theory of knowledge creation and use will be needed to guide the conceptualization and implementation the changes to marketing learning. He also calls for ways to assess the impact and success of various initiatives, prioritize initiatives, and allocate resources to them.

Market Knowledge

The ability to generate and deploy market knowledge is linked generally to firm competitive advance and success (Slater and Narver 2000; Kim and Atuahene-Gima 2010) and specifically to improved outcomes in new product development, capabilities, decision-making, and forecasting (Calantone and Di Benedetto 1988; Kim and Atuahene-Gima 2010; Srivastava, Fahey, and Christensen 2001). Market knowledge has been identified as an area where improvements are necessary and can be effective (Day 2011). Therefore, an exploration into how forecasting can be improved in support of new product development should be examined in the context of the creation and use of market knowledge for understanding and direction. Table 4 summarizes seven prominent articles that examine market knowledge. For each article, independent and dependent variables, analysis method, key findings, and future research questions are identified. In the sections that follow, information from these and other articles is used to review the evolution of market knowledge thinking, key dimensions, areas of needed improvement, areas of further study, and implications for the study of new product forecasting.

Li and Calantone (1998) make a strong connection between market knowledge and new product development and demonstrate its impact on new product advantage. Moorman (1995) also emphasizes this link, "The new product domain seems particularly well suited to examining the impact of organizational information processes" (p. 323). Li and Calantone describe market knowledge as a strategic asset or competence (capability) that leads to firm competitive advantage.

Specifically Li and Calantone (1998) state, "A customer knowledge process enhances new product advantage because it enables a firm to explore innovation opportunities created by emerging market demand and reduce potential risks of misfitting buyer needs" (p. 16). They describe market knowledge as organized and structured information about the market and consider it a higher order resource. They introduce the concept of market knowledge competence as the processes that generate and integrate market knowledge. Market knowledge competence comprises a customer knowledge process (acquisition, interpretation, and integration), a competitor knowledge process, and the marketing-R&D interface. They also identify R&D strength as a contributing factor and customers, competition, technology, and market knowledge importance as antecedents.

Table 4. Market Knowledge Literature Review Table

Source	"The Impact of Market Knowledge Competence on New Product Advantage: Conceptualization and Empirical Examination," Li and Calantone 1998	"Market Information Processing and Organizational Learning," Sinkula 1994
Purpose / Research Question	Empirically test a conceptual model of market knowledge competence and new product performance.	Characterize the relationship between market information processing and organizational learning.
Theoretical Elements	Market performance (DV) New product advantage (DV) Market knowledge competence: i) Customer knowledge process (acquisition, interpretation, and integration) ii) Competitor knowledge process ii) Marketing-R&D interface R&D strength Antecedents (Customer, Competition, Technology, and Market knowledge importance)	Organizational learning Market based organizational learning Market information processing i) Acquisition ii) Distribution iii) Interpretation iv) Organizational memory Market knowledge/intelligence
Analysis	236 completed surveys from three waves of survey mailings to 1074 U.S. software companies listed with an information service provider. Multi-item scales tested for reliability and validity. Significance tests of measurement (CFA) and structural (SEM) models. Nine hypotheses tested.	Literature review and conceptual development of market information processing and corresponding relationship with organizational learning. Organizational learning (acquisition, distribution, and interpretation) leads to organizational knowledge (stored memory) and use.
Key Findings	Market knowledge competence factors and R&D strength positively affect new product advantage. New product advantage positively affects market performance. Market knowledge importance positively affects Market knowledge competence factors.	Market-based organizational learning as organizational learning regarding markets as the fundamental bases of competitive advantage. Market information processing is influenced by organization age, size, and learning orientation.
Future Research	Can market knowledge competence contribute to improvements in other areas of new product development? Future studies should investigate additional new product outcome measures. What mechanisms exist to support market knowledge competence?	Further research on the interplay amongst information capabilities, the knowledge creation process, and managers' use of market research information. Regarding marketing knowledge development, insights are needed into how organizations can better develop and use market learning leading to improved marketing performance.

Table 4. (continued)

Source	"Organizational Market Information Processes: Cultural Antecedents and New Product Outcomes," Moorman 1995	"Intelligence Generation and Superior Customer Value," Slater and Narver 2000
Purpose / Research Question	Identify and empirically test organizational information processes, their cultural antecedents, and their impact on new product outcomes.	Describe four different intelligence-generation strategies and demonstrate how each contributes to the creation of superior customer value.
Theoretical Elements	New product performance, timeliness, and creativity (DVs) Market information processes i) Information acquisition ii) Information transmission iii) Conceptual use of information iv) Instrumental use of information Market intelligence Internal/external orientation Informal/formal governance	Product Quality (DV) New Product Success (DV) Customer Satisfaction (DV) Sales Growth (DV) Modes of intelligence generation: i) Market focused ii) Collaborative iii) Repetitive experience iv) Experimentation Market dynamism (CV) Competitive hostility (CV)
Analysis	92 completed surveys from mailings to 396 divisions of the top 200 U.S. advertisers listed in *Ad Age*. Multi-item scales tested for reliability and validity. Significance tests of measurement (CFA) and regression models (OLS). Seven hypotheses tested.	66 completed surveys from mailings to 995 of the largest U.S. electronics firms. Multi-item scales tested for reliability and validity. Nine hypotheses are tested through OLS regression.
Key Findings	Organizational market information processes are distinct from individual information processing activities. Some aspects of organizational orientation and governance influence how firms process and use market information. Only conceptual and instrumental use of information impact outcomes.	Approximately half of the hypothesized relationships between the modes of intelligence generation and outcome DVs are significant – all four modes do affect at least one outcome variable. Market dynamism affects outcome variables but competitive hostility does not.
Future Research	Better understand how i) differences in organizational vs. individual levels, ii) culture and iii) systems may impact components of market information processes.	The need for opportunities and forums to share intelligence is identified as well as the opportunity to leverage information technology to facilitate rapid information sharing.

Table 4. (continued)

Source	Organizational Learning: The Contributing Processes and the Literatures," Huber 1991	"A Model of Marketing Knowledge Use Within Firms," Menon and Varadarajan 1992
Purpose / Research Question	Contribute to a more complete understanding of organizational learning by elaborating on four integrally linked constructs and identifying opportunities for further research integration.	Propose a model to understand the informational and organizational factors that affect marketing knowledge use in firms.
Theoretical Elements	Knowledge acquisition (5 subunits) Information distribution Information interpretation (4 subunits) Organizational memory (2 subunits)	Type and extent of knowledge utilization (DV) Environmental factors Task complexity (2 items) Organizational factors (3 items) Informational factors (3 items) Individual factors (2 items)
Analysis	Broad, multi-field literature review integrating and synthesizing varied information on organizational learning and its key dimensions.	Literature review and conceptual analysis of multidimensional factors affecting knowledge use and their relationships and the presentation of 19 propositions.
Key Findings	Organizational members and units serve as knowledge acquirers through multiple modes. Learning can be improved by moving information from those have it to those that need it within an organization. Organizational learning requires shared understanding or interpretation across members. The application of stored knowledge faces numerous organizational impediments.	Although the characteristics of knowledge are important determinants of its utilization, the characteristics of the firm are just as important, if not more important. Knowledge use is influenced by environmental, organizational, task, and individual factors and communication flows. Knowledge use is also influenced by information cost, credibility, and usefulness. There are three types of knowledge use: action oriented, knowledge enhancement, and affective.
Future Research	How do those that possess information and those that need it connect and share within an organization? Empirical research needed on the dynamic of information processing as an organizational vs. an individual process is needed. What are the antecedents to information processing in organizations?	Valid and reliable scales are needed to measure knowledge utilization. Empirical study is needed to validate the influence and relative importance of the multiple factors identified. There is no consideration of the process systems, or tools that actually facilitate knowledge utilization.

Table 4. (continued)

Source	"Market Intelligence Dissemination Across Functional Boundaries," Maltz and Kohli 1996
Purpose / Research Question	Assess the effects of the interfunctional dissemination process on market intelligence reception and use, identify factors that influence the dissemination process, and explore the influence of trust in the source of intelligence.
Theoretical Elements	Market Intelligence Use (DV) Perceived Intelligence Quality (DV) Dissemination Process (2 items) Trust in Sender Receiver characteristics (2 items) Interpersonal factors (2 items) Interfunctional factors (2 items) Environment factors (2 items)
Analysis	788 completed surveys from mailings to 1061 U.S. high-tech companies listed with an information service provider. Multi-item scales tested for reliability and validity. 23 hypotheses tested using three-stage least squares regression.
Key Findings	Dissemination frequency and formality have curvilinear effects on perceived intelligence quality and formality has a positive effect on market Intelligence use. Perceived intelligence quality also has a positive effect on market Intelligence use. Fourteen of the antecedent effects also have significant influence on the dependent variables.
Future Research	Effects of dissemination should be examined in other industries where marketing may have more influence. Further study of the role of interfunctional distance is needed. Learning on dissemination should be integrated and tested with other literatures. Effects of dissemination should be examined for other types of market information use.

The market knowledge concept has origins in the organizational learning literature. Sinkula (1994) anchors his discussion of market knowledge in organizational learning work. He describes how organizations learn through interaction with their environments as members share information and create organizational memory in the form of shared beliefs, assumptions, and norms. Sinkula describes organizational learning as preserving knowledge so that it can be used by other individuals. He bases his definition of market information processing on Huber’s (1991) components of organizational learning:

> Knowledge acquisition is the process by which knowledge is obtained. Information distribution is the process by which information from different sources is shared and thereby leads to new information or understanding. Information interpretation is the process by which distributed information is given one or more commonly understood interpretations. Organizational memory is the means by which knowledge is stored for future use. (p. 90)

Huber (1991) makes a useful distinction between information (as data) and knowledge as the more complex products of learning, interpretations, and beliefs. Huber further defines knowledge acquisition by the five sub elements of congenital learning, experiential learning, vicarious learning, grafting, and searching and noticing. Information interpretation is defined by the four sub elements of cognitive maps and framing, media richness, information overload, and unlearning. Organizational memory is defined by the two sub elements of storing and retrieving information and computer-based organizational memory. Slater and Narver (1995) define organizational learning as the development of new knowledge or insights that have the potential to influence behavior, and ultimately lead to improved performance. Slater and Narver (2000) describe the organizational learning process as individuals acquiring and sharing intelligence, organizational members achieving shared interpretation of the intelligence, and potential changes and actions that can result.

Marketing authors brought the organizational learning concept into the marketing field by applying it to information about markets. Sinkula (1994) uses market-based organizational learning to explain the relationship between organizational learning and market information processing. He describes market-based organizational learning as learning about markets that provides a fundamental basis of competitive advantage. Similarly, Moorman (1995) discusses market information as external information that is available to all functional areas of the firm.

The creation and use of market knowledge or intelligence is commonly referred to as market information processing in the marketing literature and will serve as a primary construct for the remainder of this dissertation. Sinkula et al. (1997) describe market information processing as the process by which information is transformed into knowledge, and they identify its components as information generation, dissemination and interpretation and its outcome as organizational memory. They emphasize the importance of market information processing in creating organizational learning. Moorman (1995) describes organizational market information processes as information acquisition, transmission, and use and market intelligence as the firm wide outcome of these processes. Moorman further describes market information processing in the following way: information acquisition is bringing information about the external environment into the organization; information transmission is formal and informal diffusion of information among relevant users within an organization; conceptual use is the indirect use or influence of information in strategy-related actions; and instrumental use is the direct application of information in making, implementing, and evaluating marketing decisions and marketing strategy-related actions. Sinkula (1994) describes market information processing as encompassing the acquisition, distribution, interpretation and storage of market information. Storage is later referred to as organizational memory. Sinkula (1994) does not require the use of information as a component of the market information processing.

Each of the market information processing elements has also been examined in depth, individually. For example, Slater and Narver (2000) examine specifically how intelligence is generated and how data is collected and given meaning within an organization. They define four modes of intelligence generation: market-focused (sensing and scanning), collaborative (partnerships and networks), experimentation, and repetitive experience (learning curve). Maltz and Kohli (1996) examine specifically how market intelligence is disseminated for understanding the environment and making and implementing decisions. They consider dissemination to be the sharing of market intelligence from marketing managers to non-marketing managers. Dissemination is defined further by its frequency (the number of information sharing events) and formality (informal or formal channels). They also identify several antecedents that affect market intelligence use directly and indirectly: receiver characteristics (organizational commitment and customer visits); interpersonal characteristics (positional power and relationship length); interfunctional relationships (rivalry and distance); environment (structural flux and market dynamism); and trust in sender. Maltz and Kohli provide empirical evidence that dissemination frequency and formality have curvilinear effects on perceived intelligence quality and formality has a positive effect on market intelligence use. These curvilinear effects are related to diminishing returns and thresholds pertaining to frequency and formality of dissemination. They also demonstrate that perceived intelligence quality has a positive effect on market Intelligence use. Sinkula (1994) refers to the product of market information processing as organizational memory and Moorman (1995) refers to it as market intelligence and finds its influence should be on decision makers across the firm not just marketing. Decision making is described as the integration of information sources and the selections among strategic alternatives.

The concept of market knowledge use has also been examined specifically. Moorman (1995) emphasizes the conceptual and instrumental use of information as a critical component of market information processing. Day (1994) also formally incorporates information utilization as a fifth element in his market sensing model (with acquisition, distribution, interpretation, and organizational memory). Menon and Varadarajan (1992) describe knowledge utilization as the extent to which is information is used directly to guide behavior and make decisions; reduce uncertainty; and effect specific changes in behavior, cognition, and affect. They propose that the type and extent of knowledge utilization be evaluated along four dimensions: individual vs. group, domain (where), level of analysis, and time frame. Menon and Varadarajan view knowledge utilization as a function of the direct and indirect effects of multiple factors including environmental factors; task complexity (variability and difficulty); organizational factors (degree of structure, information and innovation culture, and internal and external communication flows); informational factors (cost, perceived credibility, and perceived usefulness); and individual factors (prior dispositions).

Slater and Narver (2000) consider market intelligence as influencing organizational behavior in at three ways: action oriented use (solve a problem or exploit an opportunity), knowledge-enhancing use (foundation for future behavior change), and affective use (increase satisfaction with a change already made).

Several additional dimensions of marketing knowledge creation and use have been studied. Moorman (1995) describes culture as “the pattern of shared values and beliefs that help individuals understand organizational functioning and that provide norms for behavior in the organization" (p. 320). Moorman considers the impact of external/internal organizational orientation and informal/formal organizational governance and how they affect information creation and use. These align with other discussions regarding exploitive/explorative orientations. Based on the two dimensions of organizational orientation, Moorman identifies four classes of organizational cultures: adhocracy, market, hierarchy, and clan. Sinkula 1994, finds that market information processing is influenced by organization age, size, and learning orientation. Organizations are more or less open to new information and are passive or active in the acquisition of information. Slater and Narver (1995) and Sinkula, Baker, and Noordewier (1997) show that an organizations learning orientation and culture have an effect on how well market information is collected, disseminated, and used within organizations. Adams, Day, and Dougherty (1998) find that despite recognition of its importance and value in new product development, the acquisition, dissemination, and use of market knowledge can be inhibited by barriers within organizations. Acquisition is often impeded by ambiguity avoidance, dissemination by compartmentalized thinking, and use by inertia and status quo tendencies. The authors look to encouraging broad functional participation and the use of market research tools to support effective market leaning within organizations. Information processing at the organizational level versus the individual level has also been researched (Huber 1991; Moorman 1995).

Several gaps in market knowledge understanding and opportunities for further study are identified in these literatures. Li and Calantone (1998) ask if market knowledge competence can contribute to improvements in other areas of new product development. They also ask about what mechanisms exist to support market knowledge competence within organizations? Sinkula (1994) suggests further research in the area of market knowledge creation and its use (the supply and demand). Huber (1991) and Sinkula (1994) consider the problem of where information resides or is stored, how it is retrieved for use, and the role of technology in facilitating this connection and application.
In terms of level of analysis, Moorman (1995) and Huber (1991) raise interesting questions about how organizational and individual levels of information processing are related, how individual level processing becomes organizational, and whether there are other intermediate levels that may be useful. Adams, Day, and Dougherty (1998) indicate the need to encourage broad functional participation and the use of market research tools to support effective market learning within organizations.

This review of the literature on market knowledge creation and use uncovers four key dimensions of market information processing that should be considered when studying how capabilities, new product development, and forecasting may be related: knowledge generation or acquisition, information dissemination or distribution, information interpretation and use, and market knowledge or intelligence as the codified or stored knowledge. These dimensions should also contribute to understanding how prediction markets may improve forecasting and new product development outcomes.

Marketing Decision Making

Decision making plays an important role within the capabilities, new product development, and market knowledge literatures. Effective decision making is linked to new product advantage, success, and market performance (Slotegraaf and Atuahene-Gima 2011; Atuahene-Gima and Li 2004). For example, Calantone and Di Benedetto (1988) find that two of the important factors leading to product success are clearly market intelligence and decision making. New product development itself is characterized as a deliberate, disciplined, problem-solving process that involves multiple decisions throughout the process (Krishnan and Ulrich 2001; Brown and Eisenhardt 1995).

There are two primary decisions in new product development from a marketing perspective that are both supported directly by forecasting: screening and selecting new concepts to proceed within the new product development process (so called go/no-go decisions) (Kahn et al. 2012; Thomas 1987; Calantone and Di Benedetto 1988) and estimating eventual market demand to support production, distribution, and marketing planning and investment (Hardie, Fader, and Wisniewski 1998; Simon 2009). For example, Mahajan and Wind (1988) discuss models that are "designed to assist management in evaluating concept-product options and forecast their likely performance" (p. 343).

March and Simon (1993) consider the flow of information that supports decision making as the overarching issue in the study of organizations. They find there are two types of decisions: individual decisions about participation in the organization and decisions that direct how the organization will plan and execute its business. Regarding new product development, Krishnan and Ulrich (2001) classify decisions as concept development, supply-chain design, product design, and product launch. They observe that, although the details may vary across firms, these basic decision types are consistent. Wierenga, Van Bruggen, and Staelin (1999) describe the decision situation as being comprised of three basic characteristics: the problem (degree of structuredness), the environment (market dynamic), and the decision maker (cognitive style).

Marketing has a well-established and expected role regarding decision making within new product development both through market information provided and in making and influencing decisions (Ehrman and Shugan 1995; Verhoef and Leeflang 2009; Kahn 2002). Calantone and Di Benedetto (1988) find, not only that marketing involvement in new product development is a critical determinant of product success, but also that lack of marketing involvement is a key reason for failure. Specifically they propose, “A firm possessing strong marketing resources and skills will be in a better position to perform adequately marketing activities and market intelligence activities particular to the new product” (p. 206).

A central dimension of the decision making literature is decision support systems or decision aids. Wierenga, Van Bruggen, and Staelin (1999) refer to these broadly as marketing management support systems (MMSS) and find they include marketing information systems, marketing models, marketing expert systems, and marketing neural networks. Specifically they find, “Decision aids support marketing managers in preparation, execution, and evaluation of marketing activities” (p. 196). They also observe that most MMSSs are complex quantitative optimization models, use available historic data, and are primarily concerned with forecast accuracy. Cohen, Eliashberg, and Ho (1997) discuss how decision support systems can improve the new product development process as tools to integrate data and model key decision outcomes such as multi-stage forecasts. They describe forecasts as a critical input to decisions as products move through the new product development process; this is especially true in the fast paced, high uncertainty, consumer packaged foods business. They propose a DSS that performs multi-stage forecasts by integrating group judgmental, consumer product testing, and product-market analog methods.

Just as the need for improvements in forecasting methods has been identified, so has the need for improvements in decision making. Day (2011) describes how information overload has contributed to the loss of marketing's ability to make decisions, process information, and prioritize tasks. He describes traditional decision processes as cautious and slow and finds that, unless new tools and approaches are adopted, business performance will continue to suffer. He finds that the demands of the turbulent marketplace require decision making to be more timely and flexible, what he calls just-in-time decision making. In terms of improving decision making processes there is again an emphasis on decision support systems and tools. Krishnan and Ulrich (2001) describe how product development is a process involving hundreds of decisions that can be usefully supported by knowledge and tools. They call for more research into the benefits of new tools to manage product knowledge and support decision making and how they can be expanded within the new product development process. Wierenga, Van Bruggen, and Staelin (1999) observe that the majority of MMSS have been designed for highly structured problems, in stable environments, and existing databases, but there have been very few decision aids designed for situations with low structured problems, in dynamic markets, with limited available data. There is a need for these tools. They also find that there is a need to study knowledge-based systems that do not rely on quantitative modeling of data and that can incorporate the judgments of managers:

> It has been demonstrated that the combination of human judgment and MMSS is a very powerful partnership … More insight is needed in how to accomplish the match that gets the most out of this combination of modeling and managerial judgment…We encourage others to study the managerial decision-making process and to provide new insights as to how to blend managerial knowledge with decision aid output to arrive at better decisions. (p. 203)

This is interesting to the problem and questions examined in this dissertation as prediction markets can be considered as effective decision support systems or tools that satisfy these needs (Berg and Rietz 2003). As will be discussed in following sections, prediction markets can use market knowledge to make forecasts to support marketing decisions in new product development and other areas such as supply chain and marketing return on investment.

Forecasting

Forecasting is the primary area of study in this dissertation. Forecasts process market knowledge and serve as a key input to marketing decision making. In order to effectively understand forecasting, a broader understanding is needed of the topic, and its study, measurements, developments, issues, and research directions. The issues and learning presented in this section will help to define constructs, measurement relationships, and field test parameters for the remainder of this study. Forecasting plays a critical role in the success of new product development and launch as well as business planning and success in general. Makridakis (1996) describes the role of forecasting as indispensable for business planning. He observes that being able to predict future market conditions is a prerequisite for success which "brings forecasting to the forefront of management" (p. 513). Calantone and Di Benedetto (1988) find that marketing activities including sales projections to determine future market potential must be performed well to ensure product success. Fildes and Hastings (1994) make a similar observation on the importance of forecasting:

> Market and sales forecasting are fundamental to the theory and practice of the marketing function. Without a sales forecast, in the short term, operations can only respond retroactively, leading to lost orders, inadequate service and poorly utilized production resources. In the longer term, financial and market decision making misallocate resources so that the organization's continuing existence may be brought into question. (p. 1)

Table 5 summarizes nine prominent articles that examine forecasting. For each article, independent and dependent variables, analysis method, key findings, and future research questions are identified. In the sections that follow, information from these and other articles is used to review the evolution of forecasting thinking, key dimensions, areas of needed improvement, areas of further study, and implications for the study of new product forecasting. As indicated on Table 5, important dimensions of forecasting include obtaining and preparing data; evaluating, selecting, and implementing methods used; time horizon; product and market scope; level of aggregation, organizational roles and responsibilities, accuracy or error, and uncertainty. Three areas of forecasting theory are reviewed in this section: general practice and improvements, new product forecasting, and combining forecasts; Table 5 is organized along these same dimensions.

Table 5. Forecasting Literature Review Table

Source	"Standards and Practices for Forecasting," Armstrong 2001b	"Findings from Evidence-Based Forecasting: Methods for Reducing Forecast Error," Armstrong 2006
Purpose Research Question	Summarize extant knowledge about forecasting process and outcomes.	Summarize progress made over the past 25 years with respect to methods for reducing forecasting error and identify the best forecasting procedures to use under given conditions.
Theoretical Elements	Formulating the problem (setting objectives and structuring problem) Obtaining information (collecting and preparing data) Implementation (selecting, applying, and combining methods) Evaluation (evaluating methods and assessing uncertainty) Using forecasts (presenting and learning)	Ex ante forecast accuracy (reduction in error) Classification of methods and analysis: i) Well-established ii) Promising with limited evidence iii) Tested with little gain in accuracy iv) Widely used but subject to little testing
Analysis	139 forecasting principles drawn from Principles of Forecasting (Armstrong 2001a) and subject to collaborative review and refinement with 20 experts over three year period.	Examination of empirical studies that used multiple hypotheses to compare alternative forecasting methods. Critical review of 17 methodologies and evidence of their efficacy. Analysis segregated into all data, cross-sectional data, and time series data.
Key Findings	By examining forecasting processes and improving them, managers may increase accuracy and reduce costs. Forecasters often ignore common sense and received wisdom with few principles followed in practice.	Well-established methods have been shown to improve accuracy: combining forecasts and Delphi for all types of data; causal modeling, judgmental bootstrapping and structured judgment for cross-sectional data; and causal models and trend-damping for time series data. Additional promising methods for improving accuracy are also listed for cross-sectional and time series data.
Future Research	Conduct experiments to evaluate forecast processes and outcomes. Future application and study of forecasting principles will refine existing principles and add new ones.	"Multiple hypotheses tests should be conducted on widely used but relatively untested methods such as prediction markets, conjoint analysis, diffusion models, and game theory." There needs to be testing of prediction markets against other structured group methods.

Table 5. (continued)

Source	"An Exploratory Investigation of New Product Forecasting Practices," Kahn 2002	"Factors Affecting New Product Forecasting in New Firms," Gartner and Thomas 1993
Purpose Problem Research Question	Identify current industry practices and attempt to identify preferable practices related to new product forecasting (NPFC).	Identify factors that influence ability to accurately forecast new product sales. Examine a broader set of factors used to explore sources of error.
Theoretical Elements	Forecast accuracy Department responsibility (8 items) Department involvement Technique usage (20 items) Type of new product (6 items) Time horizons Forecast satisfaction	Forecast error (DV) Decision maker expertise and motivation Marketing research budgets Data sources and methods Marketing program factors Environmental factors Competitive/industry factors
Analysis	Mail survey of 144 practitioner members of the PDMA. Questionnaire to gather opinions on the seven topics. Data analysis included descriptive statistics and significance tests.	Mail survey of 113 computer software firms using scaled questions. Comparison of factor means between more and less accurate firms and discriminant analysis of drivers of accuracy. Hypothesized influence of several independent factors on forecast error
Key Findings	Relatively low average accuracy rate for NPFC (58%). Marketing primarily responsible for forecasts in 62% of the cases. Strong preference toward less sophisticated, qualitative techniques combined with market research. More than half of companies satisfied with NPFC process.	More accurate forecasts are likely to result from firms with founders that have more marketing experience, place higher importance on generating an accurate forecast, spend more on marketing research to achieve it, use data sources and methods closer to the consumer, use more methods, and enter less volatile markets.
Future Research	Relatively low accuracy rate for NPFC, continued study of NPFC process improvements is warranted. What are the best types of NPFC techniques to support the launch phase? How can multiple techniques and departments be involved?	What are other antecedent sources of forecast error and their impact? How do different types and levels of expertise affect forecast accuracy? Further research into different types of data sources and methods needed in new product process.

Table 5. (continued)

Source	"Forecasting New Product Market Potential: Combining Multiple Methods," Thomas 1987	"New Product Forecasting Models-Directions for Research and Implementation," Mahajan and Wind 1988
Purpose Research Question	Introduce guidelines to implement multiple method (combined) forecasting.	Assess strengths and weaknesses of the currently available new product forecasting methods and outline an agenda for further development and implementation.
Theoretical Elements	Market potential as key construct Eight factors used to forecast market potential: Product definition Sales volume measure Purchase measure Customer group definition Geographic area measure Time period of measure Marketing environment Marketing program	New product forecasting models Three data sources: management and expert judgments, analogous products, and consumer responses Focus is limited to consumer-based new product forecasting models Most appropriate products and conditions Sales estimates Diagnostics of marketing and environment factors Impact on firm's finances and products Implementation and cost factors
Analysis	Conceptual development of market potential definition, multiple measures, and how to combine them.	Review of literature describing leading forecasting models and propose an agenda for further development and implementation of these models.
Key Findings	Carefully define the parameters of market potential and its contributing factors, obtain 2-6 independent forecasts, and combine them in a systematic way.	There are several new product development stages where forecasting models can and should be used. There are many models, no agreement on evaluation criteria or best models, considerable variation in models, insufficient published comparison of models, and little attention to predictive accuracy.
Future Research	More effort should be invested in determining good forecasting methods early in the new product process to achieve better go/no go decisions.	External, empirical validation of models needed. Combination of forecasts needed. Models needed to forecast truly innovative products. Models based on new data bases needed. Testing of emerging expert forecasting systems and models with global capability needed.

Table 5. (continued)

Source	"Combining Forecasts: A Review and Annotated Bibliography," Clemen 1989	"Averages of Forecasts: Some Empirical Results," Makridakis and Winkler 1983
Purpose Research Question	Extensive literature review of combining forecasts covering early work, seminal papers, contributions from other disciplines, and recent developments.	Empirical investigation of the impact of the number and choice of forecasting methods on the accuracy of simple averages.
Theoretical Elements	Forecast accuracy Averaging forecasts Incremental information Judgmental forecasting Group processing and judgments Probability distributions	Forecast accuracy Forecasting methods Time horizon Combination composition
Analysis	Review of over 200 journal articles and monographs regarding theoretical background, major areas of contribution, applications, and future areas of research needed.	Fourteen different forecast methods were applied against 1001 time series data from the M-Competition. Data reflects industry, firms, divisions, macroeconomic variables, and demographics over three time horizons. MAPE computed for various combinations of methods.
Key Findings	Significant research evidence dating back to 1967 that combining multiple forecasts leads to increased forecast accuracy. Contributions to current combining theory has come from psychology, statistics, management science, and forecasting. Simple averaging methods often work better then more complex models.	Using averages of forecasts provides considerable practical benefits in terms of improved forecasting accuracy and decreased variability of accuracy. The average MAPE consistently declines as the number of methods increases. The marginal impact of including an additional method decreases as the number of methods increases. The choice of the best method becomes less important when averaging.
Future Research	Opportunity to build models that can accommodate wide variety of forecasts and information. Need to find ways to make combining easy and efficient. Decision makers must be encouraged to use technology to combine forecasts and use them in decision making.	Combining objective forecasts with subjective forecasts is a promising area requiring further research. A great deal can be gained by studying the properties of various types of combined forecasts.

Table 5. (continued)

Source	" Combining Forecasts," Armstrong 2001d
Purpose Research Question	Summarize results from the literature on theory and empirical studies of combining forecasts.
Theoretical Elements	Forecast error measures (MAPE) Methods and data Number of forecasts Procedures for combining Uncertainty Forecast time horizons
Analysis	Conceptual review of 57 articles and meta-analysis of data from 30 of these studies. Percent error reduction computed across results of studies.
Key Findings	In 30 empirical comparisons, the reduction in ex ante errors for equally weighted combined forecasts averaged about 12.5% and ranged from 3% to 24%.
Future Research	Combine forecasts based on different data and methods; use multiple methods (five or more); use formal procedures for combining; use equal unless there is reason and guidance to use unequal weighting. Combine forecasts when uncertain about situation or method and when trying to avoid large errors.

The focus of forecasting research in general has been on the process and methods that produce forecasts and on the accuracy of their outcomes. Armstrong (2001b) performs an in-depth review of the forecasting process and identifies 139 process dimensions as principles for improved results. The principles are structured as i) formulating the problem (setting objectives and structuring problem); ii) obtaining information (collecting and preparing data); iii) implementation (selecting, applying, and combining methods); iv) evaluation (evaluating methods and assessing uncertainty); and v) using forecasts (presenting and learning). Armstrong (2006) reviews 17 forecasting methods from the perspective of well-established and proven methods versus new and alternative methods with varying degrees of evidence of effectiveness - these methods are listed on Table 6. Among these methods Fildes and Hastings (1994) observe from their review of the literature that structured judgment methods are the most common, “Subjective forecasting techniques based on expert, usually executive, opinion are more widely used than any of the quantitative approaches to forecasting common in the management science literature” (p. 1).

Forecast accuracy is predominantly measured as forecast error. The forecasting literature indicates multiple measures of forecast accuracy; several of the more common measures include correlation with actual outcomes, absolute error, mean absolute error, absolute percentage error, mean absolute percentage error, and standard deviation of error (Dalrymple 1987; Wolfers and Zitzewitz 2004; Armstrong 2006; Armstrong and Collopy 1992; Mahmoud 1994). The most common methods are relative measures of accuracy provided by absolute percentage error (APE) and mean absolute percentage error (MAPE) (Armstrong and Collopy 1992; Armstrong 2001c).

Table 6. Armstrong Overview of Forecasting Methods

Well-established methods All types of data ▪ Combining forecasts, Delphi Methods for cross-sectional forecasting ▪ Causal models, Judgmental bootstrapping, Structured judgment Methods for time series forecasting ▪ Causal models, Damped trend
Promising findings with limited evidence on accuracy Methods for cross-sectional data ▪ Damped causality, Simulated interaction, Structured analogies, Judgmental decomposition Methods for time series data ▪ Segmentation, Rule-based forecasting, Decomposition by causal forces, Damped seasonal factors
Tested areas with little gain in accuracy Time series forecasts ▪ Data mining, Neural nets, Box–Jenkins methods
Widely used methods that have been subject to little testing All types of data ▪ Prediction markets Cross-sectional data ▪ Conjoint analysis, Game theory, Structured judgmental adjustments Time series data ▪ Diffusion models

Source: Armstrong 2006

These measures and their use are discussed further in the methodology section of Study I.

Unfortunately, firms often get forecasting wrong. In spite of the availability of sophisticated systems and support, effective sales forecasting is an area where companies struggle to be proficient (Mahajan and Wind 1992). This is usually because they do not employ good forecasting practices (West 1994; Armstrong 2001b). This is in part because sales forecasting is not treated as a priority function within corporations, as a result, forecasting is often unsophisticated and underperforming (Dalrymple 1987; West 1994). Flawed analysis, high error rates, and poor decisions frequently result in massive amounts of wasted human effort and money (Kahn 2002). This hurts both a company's growth potential and profitability. A frequent observation is that poor results are due to limited use, in practice, of available formal forecasting procedures proven to improve forecasting results (Fildes and Hastings 1994; Armstrong 2001a). This is the basis of the most common call for research and action, implementing and testing established and emerging techniques to improve performance and advance our understanding (Armstrong 2001a and 2006; MSI 2012-2014).

New Product Forecasting

Forecasting is so important to the new product process that there is a body of literature dedicated to it. Three of the articles summarized in Table 5 are new product forecasting articles. New product forecasting is described in the literature as important not only to the new product process, but also to the success of the firm overall. Mahajan and Wind (1988) observe the following:

> Rapid technological advances, changing market conditions and global market competition have made it imperative for companies to be more

> focused and innovative in their search for and development of new products. Each new product is expected to play a key strategic role in the marketplace - either to defend a market share or to gain and maintain a market share. In this context, new product forecasting models have and can play a critical role in reducing the odds against failure in the marketplace. (p. 356)

In developing and launching new products and programs, forecasting is necessary to know which ventures to pursue and what their business impact will be (Wind and Mahajan 1997; Rao and Bharadwaj 2008). Effective forecasting is needed to determine the right quantity of product to produce in order to not over or under supply and to maximize profit (Jain 2007). Kahn (2002) emphasizes the importance of new product forecasting during the commercialization and launch stage. Because manufacturing, logistics, marketing, sales, and finance decisions rely on this information, errors can have significant business impact. Forecasting for new products is more difficult than forecasting sales of established products due to lack of historic data and uncertainties about consumers, competitors, and other market factors (Thomas 1987; Mahajan and Wind 1988). In line with these observations, there is wide agreement that new products forecasting does not have a high success rate (Kahn 2002). Simon (2010) observes that in the CPG industry only 15% of new products are still on the shelf two years later and error rates are often much higher for new items compared to existing item. Long term planning horizons and optimistic new product teams are offered as two additional reasons for low accuracy rates.

Combining Forecasts

The concept of combining forecasts relates to this dissertation on two levels. First, following from the recommendations in the literature, Study I will combine forecasts as part of its comparative accuracy analysis. Second, on a higher level, the whole premise of collective intelligence is an extension of combining judgments from multiple sources that have different information and methods. A prediction market does this with a large pool of forecasters in a very systematic structured way. Huber (1991) captures this idea at the organizational level when he observes that "combining information from different subunits leads not only to new information but also to new understanding" (p. 101). Armstrong (2001c) offers the following definition for combining forecasts, "Combining forecasts, sometimes referred to as composite forecasts, refers to the averaging of independent forecasts. These forecasts can be based on different data or different methods or both. The averaging is done using a rule that can be replicated, such as to take a simple average of the forecasts" (p. 1). There is much support in the forecasting literature regarding the benefits of improved accuracy and reduced variance that result from combining forecasts (Makridakis and Winkler 1983; Mahajan and Wind 1988; Gartner and Thomas 1993; Jose and Winkler 2008; Batchelor and Dua 1995; Clemen 1989). Table 5 summarizes three prominent articles regarding combining forecasts. Mahajan and Wind (1988) observe, "The recent literature in forecasting is replete with studies indicating that forecasting accuracy improves when combining results from the various models" (p. 351). Armstrong (2001c) observes that "combined forecasts are more accurate than the typical component forecast in almost all situations studied to date" (p. 8). Batchelor and Dua (1995) find that combining forecasts can reduce error by as much as 25% and combining as few as two or three forecasts can reduce errors in 67% of the cases.

One of the main findings is that simple averages work better than more complicated and sophisticated combining models and are easier to understand and implement (Clemen 1989; Jose and Winkler 2008). Gartner and Thomas (1993) and Armstrong (2006) both find that simple averages (equal-weights combining) improve forecast accuracy and reduce variability better than weighted average methods. Makridakis (1983) finds in his study that a simple average outperformed six other individual forecast methods and the weighted average. He also finds that accuracy tends to increase with more methods averaged but with diminishing improvement at higher numbers of forecasts. The benefits come from weakness in one method being counterbalanced by the strengths of another (Thomas 1987), the errors made by one method not being correlated with a different method (Batchelor and Dua 1995), the features of each model being exploited (Mahajan and Wind 1988), and the ability to capture unique information available in each approach (Clemen 1989; Makridakis and Winkler 1983). To maximize the benefits described here, one should attempt to combine forecasts that are based on methods and data that differ substantially (Armstrong 2006). Makridakis and Winkler (1983) also observe that using combined forecasts is safer and less risky than using a single method. The new product forecasting literature also highlights the benefits of combining forecasts to address the challenges and uncertainty associated with new products (Armstrong 2001d; Mahajan and Wind 1988; Gartner and Thomas 1993).

There are numerous calls for research into the methods and benefits of combining forecasts. For example, Makridakis and Winkler (1983) state, “We believe that a great deal can be gained by studying the properties of various types of combined forecasts…using averages of forecasts provides considerable practical benefits in terms of improved forecasting accuracy and decreased variability of accuracy” (p. 995). With regard to new products Mahajan and Wind (1988) also state, “We need to explore the utilization of combining results for new product forecasting” (p. 351). In general, there are calls in the marketing literature for marketing to improve its analytical metrics, methods, and skills; in particular, its capability to understand the financial consequences of marketing actions (Rao and Bharadwaj 2008; Verhoef and Leeflang 2009). This includes calls for improvements in existing demand forecasting methods (Mahajan and Wind 1992). In their research of firms, Mahajan and Wind (1992) find that, even though concept testing and pre-market volume forecasting were considered the two most important activities in new product development, they were performed most infrequently. They conclude that new product development processes need more formal and quantitative approaches, including better forecasting models in support of activities including concept screening and business analysis. There is also a need to append measures of risk or uncertainty to forecast point estimates. This is needed to support more sophisticated assessment and investment decisions now required in marketing (Rao and Bharadwaj 2008)

Marketing may be able to improve analysis, forecasting, and decision making by taking advantage of innovative techniques put forth in the forecasting literature. There have been calls by researchers to introduce innovative methods into the forecasting process. MSI 2010-2012 and 2012-2014 research priorities recommend looking for conceptual frameworks and tools from other disciplines that may enhance traditional methods. Wind and Mahajan (1997) state, “Researchers should integrate the traditional marketing research approaches with unconventional ways of obtaining the voice of the customer and integrate the results of the research with appropriate modeling (i.e. forecasting, simulations, and optimization)” (p. 10). Prediction markets have been suggested as an alternative method to improve forecasting within firms (Armstrong 2006; Van Bruggen et al. 2010; Spann and Skiera 2003; Gruca, Berg, and Cipriano 2003). Armstrong (2006) performs an exhaustive review of traditional and emerging forecasting techniques with descriptions, assessments, and calls for further application and testing of certain methods. The techniques are presented in Table 6; prediction markets, listed in the last section, are one of the methods identified for additional testing. Armstrong suggests it would be useful to test prediction markets against other traditional methods in the realm of marketing. He observes that there has been little research into prediction markets and most comparative testing that has been done has been in other domains. Armstrong (2006) states, “Over the past quarter century, little research has been done to improve our knowledge about the use of prediction markets. It would be useful to test prediction markets against other structured group methods...Nevertheless, we could learn much more about the conditions under which they are most useful” (p. 593). The next section will examine prediction markets as a collective intelligence application that can improve marketing forecasting outcomes in new product development and other important areas.

Prediction Markets

As the predominant form of collective intelligence today, prediction markets will serve as the application studied and tested as a potential solution for improved forecast accuracy. The study of prediction markets has appeared in a diverse set of literatures comprising law, economics, public policy, decision making, political science, management, finance, information systems, engineering, innovation management, risk, education, and psychology. Prediction markets have evolved over the past 25 years from complicated stock trading based systems to more user friendly systems. Berg, Nelsen, and Rietz (2008) describe prediction markets as those run for the primary purpose of using the information content in market values to make predictions about specific future events. Over this time, much learning about and support for prediction markets has developed. For example, Kenneth Arrow et al. (2008) make the following argument, “There is mounting evidence that such markets can help to produce forecasts of event outcomes with a lower prediction error than conventional forecasting methods. The range of applications is virtually limitless—from helping businesses make better investment decisions to helping governments make better fiscal and monetary policy decisions” (p. 877). In addition, Surowiecki (2005) describes decision markets as well suited to companies:

> They circumvent the problems that obstruct the flow of information at too many firms: political infighting, sycophancy, and confusion of status with knowledge. The anonymity of the markets and the fact that they yield a relatively clear solution, while giving individuals an unmistakable incentive to uncover and act on good information, means that their potential value is genuinely hard to overestimate. (p. 222)

History of Development and Use

Some of the earliest research into prediction markets was work on the problem of information aggregation by Edward Chamberlin in 1948 and then Vernon Smith in 1962. Their research focused on alternative market mechanisms that could effectively combine supply and demand of information. Charles Plott and Shyam Sunder extended on Chamberlin's and Smith's experiments to develop one of the original prediction markets that aggregated information and forecasted the value of a stock (Ho and Chen 2007). The main stream of academic literature on prediction markets emerged during the early 1990s lead by the research of Robin Hanson, Robert Forsythe and colleagues, and Berg and colleagues. Forsythe and Berg studied the market dynamic of the Iowa Electronic Market (IEM) established by the University of Iowa's Tippie College of Business in 1988 (Ho and Chen 2007). This not-for-profit exchange focuses primarily on predicting outcomes of political events, such as presidential elections. Still running today, it is one of the most recognized large scale applications of prediction markets.

Based on the success of the Iowa Electronic Market, political markets were established in other countries and several business applications were tested and written about in the late 1990s and the early 2000s (Tziralis and Tatsiopoulos 2007; Ho and Chen 2007). Since 1988, the IEM has also run markets predicting outcomes of box office receipts, earnings reports, and stock prices and returns (Berg, Neumann, and Rietz 2009).

Applications and Tests

Many of the first empirical tests of prediction markets focus on predicting political, finance, movie, and sports outcomes (Armstrong 2006). Almost all of these studies conclude that prediction markets are as good as, and, in many cases, better than existing methods for predicting outcomes (Berg and Rietz 2003; Berg, Nelson, and Rietz 2008; Wolfers and Zitzewitz 2004; Wolfers and Zitzewitz 2006; Arrow et al. 2008). For example, Wolfers and Zitzewitz (2004) conclude, "In the political domain…the Iowa Electronic Markets…have yielded very accurate predictions and also outperformed large scale polling organizations" (p. 112). Similar results in these areas have driven interest in applying prediction markets to business decisions. In the academic study of business, three empirical studies of prediction markets have received the most attention. Hewlett-Packard used internal prediction markets in 1996 (Ho and Chen 2007) and 2002 (Wolfers and Zitzewitz 2006) to forecast sales of new and existing products. Intel developed a prediction market to supplement their existing forecasting processes in 2005 (Hopman 2007). And Google launched an internal prediction market based on the Iowa Electronic Markets to forecast several different business outcomes also in 2005 (Cowgill, Wolfers, and Zitzewitz 2009). Overall, prediction markets performed as well as or better than traditional forecasting methods in these tests regarding estimates and error rates. In general, these authors conclude that prediction markets perform very well; they should be considered a part of future forecasting programs; design improvements should improve accuracy; and additional tests should be made in business settings.

Hewlett-Packard's 1996 field test of prediction markets compared market based product forecasts to forecasts using existing methods (Ho and Chen 2007). Using a measure of forecast error, the study found prediction markets were more accurate in six out of eight forecasts. The authors predict that with more participants the results could be improved. In part of their argument for the use of prediction markets, Ho and Chen discuss the results of analyses of the Hollywood Stock Exchange (HSX) by Elberse and colleagues. Based on 92 movies released prior to 2005 they found a correlation of 0.94 between predicted and actual box-office returns.

In 2003, Gruca, Berg, and Cipriano compared the ability of the IEM to predict movie box-office receipts to a lab survey with students. Based on a correlation of 0.98, the authors found that the IEM was able to accurately predict the information from the survey based forecasts. Gruca and colleagues also found the variability of the prediction market forecast to be significantly lower than the survey's variability. The IEM and the survey predictions were also compared to actual results for box-office receipts using a measure of mean absolute percentage error (MAPE). The MAPE scores were 0.30 and 0.33 for the IEM and the survey predictions respectively. This was not a significant difference in score, so the methods performed equally well.

Intel Corporation's 2005 study compared the performance of prediction markets against traditional Intel forecasting methods (Hopman 2007). They compared the methodologies along three criteria: accuracy, stability, and response speed. The analysis found prediction markets produced forecasts that were at least equal to their traditional forecasting methods and as much as 20% better in terms of error rate. Six out of eight forecasts fell within 2.7% of actual sales and there was as much as 20% less fluctuation than the traditional forecasting methods during the same period. In his discussion, Hopman suggests that results could have been improved with a more diverse participant pool.

In 2001, Spann and Skiera (2003) tested the ability of a virtual stock market to predict three outcomes compared to experts or established methods of forecasting: U.S.

movie gross box-office revenues, visitors and pop music single-chart positions in Germany, and usage of different services of a large German mobile phone operator. In the main study, the performance of the Hollywood Stock Exchange (HSX) was compared to two existing forecasting experts using a MAPE measure. The HSX performed better than one expert and equally as well as the other expert (insignificant difference). Similar results of equality were found for the other two tests. The authors call for additional business forecasting tests to further examine and validate the performance of prediction markets.

Although there are several accounts of widespread use and success of prediction markets within Google Corporation (Cowgill 2005; Dye 2008; Leigh and Wolfers 2007), there are only two formal assessments of their prediction markets within the academic literature. Unfortunately, neither study provides a direct assessment of the forecasting performance of Google's markets. One study examines setting the price for Google's initial public offering, comparing an IEM prediction to traditional Wall Street methods (Berg, Neumann, and Rietz 2009). Berg and colleagues found that the prediction market for the IPO price performed very well. Two types of markets were tested: a linear (proportional payoff) market and winner-takes-all (interval payoff) market. The IPO prices estimated by the prediction market were only 1.8% and 4.0% off the eventual actual price for the linear and the winner-takes-all markets respectively. These errors are compared to a 15.3% deviation for the traditional auction price setting method. The other Google study examines the flow of information within the organization and related biases using an internal market (Cowgill, Wolfers, and Zitzewitz 2009). In this study Cowgill and colleagues review performance of more than 25 IEM style markets conducted within

Google between 2005 and 2007 and make a general assessment that prices in the Google markets closely approximated eventual actual outcomes. They then focus their analysis on the nature of three biases found in their internal markets: optimism associated with newly hired employees, positive skews on days when Google stock was appreciating, and correlated trading between people that work in close physical proximity to each other.

In practice, many other companies have experimented with prediction markets to solve business information problems and drive innovation. Many of these applications have been reported in news and media including Abbott Labs, Arcelor Mittal, Best Buy, Chrysler, Corning, Electronic Arts, Eli Lilly, Frito Lay, General Electric, InterContinental Hotels, Masterfoods, Microsoft, Motorola, Nokia, Pfizer, Qualcomm, Siemens, Cisco Systems, Swisscom, Eli Lilly, Harrah's, Yahoo, General Mills, and TNT (Cowgill, Wolfers, and Zitzewitz 2009; Hopman 2007; Angrist 1995; King 2006; Lohr 2008; Hagel 2008; Dvorak 2008). To support this new activity, several service firms have emerged, including TradeSports (political futures, financial contracts, current events, sports, and entertainment), Economic Derivatives (future economic data releases), Lumenogic (political, finance, current events, sports markets, technology, and pharmaceutical futures), Foresight Exchange (political, finance, current events, science and technology events), and Hollywood Stock Exchange (movies, movie stars, and awards) (Wolfers and Zitzewitz 2004).

It is interesting to note that despite all of these activities and participation there is very little, if any, integration into the marketing discipline. Other than predicting box-office sales of new movie releases, there have been very few business oriented tests and none within a marketing context.

Benefits and Advantages

There are several benefits that can be achieved through the application of prediction markets to marketing forecasting and information problems. Payoff or reward mechanisms provide incentives that motivate participants to gather, create, and share information with the market (Berg, Neumann, and Rietz 2009). Wolfers and Zitzewitz (2006) describe how potential trading profits provide an incentive for 'information discovery'. These same incentives motivate participants to perform well in their estimates of future outcomes and associated trading activities (Hopman 2007; Ho and Chen 2007).

The anonymity of the market or exchange protects participants from the political or social consequences of disclosing true beliefs. Wolfers and Zitzewitz (2004) describe this free flow of information as 'truthful revelation'. Social consequences often produce significant biases in traditional estimation and forecasting processes within organizations (Berg, Neumann, and Rietz 2009; Cowgill, Wolfers, and Zitzewitz 2009). Similarly, Ho and Chen (2007) discuss how prediction markets benefit from "the free flow of independent information" (p. 152) because organizational barriers are removed. Berg and Rietz (2003) also describe anonymity afforded to market participants as important for producing unbiased forecasts.

The price formation mechanism of traditional prediction markets allows for the efficient and accurate aggregation and weighting of information that is normally a cumbersome and complex task (Berg and Rietz 2003; Wolfers and Zitzewitz 2004). The fact that trading activity is publicly viewable by all participants allows for instantaneous updating of market information (Spann and Skiera 2003). Essentially, the price of stocks provides feedback on the most recent information available to the market which participants can use to update their own information and update their estimates of future outcomes (Hopman 2007). Later sections will discuss new non-stock trading markets and methods that have emerged as more intuitive alternatives to the traditional price aggregation mechanism.

The combination of technology and internet systems provides the firm with access to a widely dispersed and diverse pool of participants and opinions both within and outside of the firm (Spann and Skiera 2003). The computer applications and systems that host an exchange allow for easy and low cost repetition and expansion of markets. Firms can avoid the expense of money and time associated with large representative samples of consumers or panels of experts (Ho and Chen 2007; Gruca, Berg, and Cipriano 2003).

Potential Issues

Although the reviews of prediction market performance have been favorable, they are not without pitfalls or issues. If effective buy-in is not achieved within the organization, the operation of the market and the use of its information outputs will be threatened (Hopman 2007). Because it may be viewed as an unusual or exotic technique by uninitiated management, this is especially true for prediction markets. If integration efforts are not handled well there may also be resistance from incumbent forecasting experts who may view a prediction market as a negative judgment of their performance or as competition. Adoption may also be impeded by management’s perception of prediction markets as magic black boxes that produce interesting results but without any understanding of how, when, where, or why they work. A senior research executive of the firm hosting the field study identified this issue as a major hurdle that must be solved before prediction markets could be presented to the organization as a new methodology to support decision making, "If they don't understand how it produces the results it does, they won't trust it, and they won't use the information it provides." (personal interview June, 2011)

Markets will not perform well if key design principles and requirements are violated (Ho and Chen 2007). For example, if the number of participants is too low, if there is insufficient incentive to trade and reveal information, or if anonymity is not provided, the market's ability to aggregate dispersed information into a single metric can be compromised (Wolfers and Zitzewitz 2004). In studying markets, Cowgill, Wolfers, and Zitzewitz (2009) and Wolfers and Zitzewitz (2006) found trader biases related to favorite or optimistic outcomes, extreme outcomes, trader experience and interactions, and low probability events. In their opinions these can be mostly overcome by effective market designs and experience. Hopman (2007) also found that, if there is an extended time horizon between market activity, final outcomes, and pay-outs, participants may lose interest and trading may stall.

Other Factors

There are several additional concepts that contribute to understanding prediction markets while also describing some of the benefits: information aggregation, efficient market hypothesis, non-representative participants, and managing uncertainty.

Information Aggregation

One of the most important underpinnings of prediction markets is their ability to handle the complex task of aggregating information. This is achieved through single trading prices assigned to outcomes designed into the markets. Even though participants have different levels of information accuracy, Ho and Chen (2007) conclude, “The use of price forces participants to express their thinking in a precise and common metric” (p. 151). This is how the markets merge information, average multiple opinions, and give more weight to more informed individuals (Ho and Chen 2007; Hopman 2007). In this regard, Gruca, Berg, and Cipriano (2003) suggest how, through rational expectations theory “asset markets are able to distill disparate sources of public and private information into a single measure: price” (p. 95). Other estimation processes cannot provide as precise a measure of outcomes as forecasts in the form of market-generated prices (Wolfers and Zitzewitz 2004). A theme that is often raised regarding prediction markets is the wisdom of crowds, how a large group of laymen can beat even a small number of experts (Surowiecki 2005). This observation is grounded in the statistical principle of the Law of Large Numbers (Ho and Chen 2007).

Efficient Market Hypothesis

The effectiveness of price in information aggregation has been explained by the efficient markets hypothesis, rational expectations theory, and the Hayek hypothesis (Wolfers and Zitzewitz 2006). Articles describing prediction markets reference the works of Fama in 1970 and Hayek in 1945 when describing the price mechanism of competitive markets as the most efficient method for aggregating the asymmetric information of market participants (Spann and Skiera 2003; Gruca, Berg, and Cipriano

2003). Spann and Skiera describe markets as efficient if all available information is always fully reflected in the prices. Therefore, prediction markets efficiently combine information when "the prices of these contracts perfectly aggregate dispersed information about the probability of [each outcome]" (Wolfers and Zitzewitz 2006, 1).

Non-Representative Participants

Participants of prediction markets are typically not a representative sample of the electorate or consumers to be estimated; this is not necessary. Unlike polls or surveys, participants are expected to use their information and assessments to make predictions of the behavior of the entire market rather than their own intended behavior (Spann and Skiera 2003). This removes the need for large representative samples traditionally required for marketing estimates (Gruca, Berg, and Cipriano 2003).

Managing Uncertainty

According to Wolfers and Zitzewitz (2004), prediction markets not only make forecasts of specific outcomes, but they can also evaluate uncertainty about them. The set of correctly specified contracts can provide a probability distribution of the market's expectations; this can be used to calculate the level of uncertainty surrounding specific point estimates. Similar distributions are used by Berg, Neumann, and Rietz (2009) in their work on predicting Google's IPO.

Design Details and Requirements

Much of the literature, learning, and design parameters regarding prediction markets are based on stock-trading based markets. For this reason, the discussion in this section summarizes details on how these types of markets are designed and operated.

The stock-trading markets have been criticized for their complexity and how this impedes the level and nature of participation and information revealed. To address this issue, a non-stock-trading prediction market will be introduced and described in the methodology section of the chapter for Study I. It is necessary, however, to understand the mechanism of traditional trading markets in order to understand how and why traditional prediction markets and innovative markets work. There are several common prediction market design parameters and requirements discussed in the prediction markets literature: predicted outcome definition, prediction specification, market design, participants, incentive program, market information, and integration with existing processes.

Predicted Outcome and Contract Specification

For prediction markets to be successful, the outcomes to be predicted and the contracts or stocks assigned to them must be defined specifically and clearly and be easily understood by participants (Wolfers and Zitzewitz 2004; Soukhoroukova and Spann 2005). For example, Spann and Skiera (2003) describe future events or market states as "(i) the prediction of an absolute number, for example, sales in a particular period; (ii) the prediction of a relative number, for example, market share in a particular period; or (iii) the occurrence or nonoccurrence of a particular event, for example, the completion of a development project at a particular point in time" (p. 1314). In order to make possible future outcomes tradable, contracts are assigned to them. These contracts must be defined clearly in terms of how they are linked to outcomes, how they are priced, and how they pay out at the close of the market. Contracts on predicted events can be specified based on either discrete or continuous outcomes. This specification will determine trading prices, payouts, and the prediction information provided (Ho and Chen 2007; Gruca, Berg, and Cipriano 2003; Wolfers and Zitzewitz 2006).

A prediction market based on discrete outcomes predefines mutually exclusive and collectively exhaustive outcomes (Cowgill, Wolfers, and Zitzewitz 2009) and assigns a tradable contract or stock to each outcome that trades at a specified price. A contract pays out (often $1) if, and only if, its specific outcome occurs and pays nothing ($0) if its specific outcome does not occur (for this reason these are called winner-takes-all contracts). The final trading prices of the contract can be interpreted as estimates of the probability of the corresponding outcome occurring (Gruca, Berg, and Cipriano 2003; Wolfers and Zitzewitz 2004). Outcomes can be defined as binary or interval. A binary outcome has one possible outcome that happens or does not, such as a product hitting a sales breakeven threshold or not (Wolfers and Zitzewitz 2006). An interval design may have several possible levels or categories assigned to an outcome with each level assigned its own contract. For example, sales of a new product can be divided into a range of different possible levels, only one of which will be realized. Traders holding contracts for the sales level that actually occurs are paid $1 for each contract and all other levels receive $0 pay out (Wolfers and Zitzewitz 2006). The contracts with the highest prices indicate which outcome scenario traders expect to occur, and the actual contract prices indicate the probability traders as a group attach to each outcome occurring (Berg, Neumann, and Rietz 2009; Berg and Rietz 2003). These discrete interval designs are particularly useful as they produce a probability distribution for the likelihood of the event to be predicted. This probability distribution is based on the collective intelligence of all traders through the contracts held and respective prices in each level within that outcome (Hopman 2007; Wolfers and Zitzewitz 2006).

A prediction market based on a continuous outcome defines the event to be predicted as a single outcome expressed as a continuous proportion, share, or index, such as a market share or percentage of votes. A tradable contract or stock is created for the single outcome, and the contract payout is based on the outcome that actually occurs (expressed as the proportion, share, or index). For this reason, these designs are also called share, proportional, linear, index, or expected value contracts (Berg, Neumann, and Rietz 2009; Gruca, Berg, and Cipriano 2003; Wolfers and Zitzewitz 2006). Wolfers and Zitzewitz (2004) describe the amount that the contract pays out as varying "in a continuous way based on a number that rises or falls, like the percentage of the vote received by a candidate. The price for such a contract represents the mean value that the market assigns to the outcome" (p. 109). For example, each percentage or share point of the outcome would equate to one cent in the stock's value; a 40% outcome would produce a stock value of $0.40 and a 100% outcome would produce a stock value of $1. The contract prices traders are willing to pay reflect their expectations of what the eventual proportion, share, or index will be (Berg and Rietz 2003).

Market Design

The trading mechanisms provide participants with a way to interface (Hopman 2007) with the market and match buyers with sellers. There are several ways this can occur; the most common trading mechanisms are continuous, double auction, synchronous, computerized, web-based, and anonymous (Cowgill, Wolfers, and Zitzewitz 2009; Hopman 2007; Ho and Chen 2007; Gruca, Berg, and Cipriano 2003).

Continuous trading allows participants to view the market and execute trades at any time from the market's initial opening to its final closing rather than periodic or limited access to the market and its information. Double auction trading allows participants to both submit bids as buyers and submit asking prices as sellers similar to an actual stock market. The trading mechanism executes a trade whenever buyers and sellers agree on a price (Wolfers and Zitzewitz 2004). Synchronous trading allows for all participants' buying and selling to occur directly and simultaneously. Computerized web-based trading allows participants to trade essentially from anywhere at any time (Spann and Skiera 2003). This also allows for rapid data collection, processing, and updating which is necessary for a smooth uninterrupted trading to occur. Anonymous trading allows participants to conduct trading without being identified; this was discussed early as a necessary condition for open sharing of truthful information.

Market funding pertains to how final contract holdings of participants are paid out after the market closes, trading is complete, and final outcomes are realized. This is linked closely with how contracts are specified, as discussed above. The main issue for the market initiator is the total potential financial liability related to pay outs to all participants. Markets based on discrete outcomes and double auction trading are closed markets with respect to pay outs, so the market initiator faces no financial liability. This design is also described as a zero-sum game based on unit portfolios where possible discrete outcomes are represented by contracts that pay something or nothing depending on the outcome and sum to $1 (Spann and Skiera 2003). Traders acquire contracts by purchasing bundles consisting of one of each level of the discrete outcome, and these bundles can be purchased from or sold to the market at any time for $1 (Gruca, Berg, and

Cipriano 2003). Conversely, markets based on continuous outcomes and market maker trading are open markets that can leave the market initiator open to undefined liability especially if real currency is used. One way that market initiators avoid financial liability is by rewarding participants not by cashing out the value of stocks, but by providing prizes based on the total value of their portfolio (Spann and Skiera 2003; Berg, Nelson, and Rietz 2008).

In order to control for the market manipulations and bubbles that occur in real financial markets, fees and rules can be designed into the market. Two common restrictions employed by prediction markets are maximum and minimum prices for limit orders and quotes (Spann and Skiera 2003), and not allowing short selling (Cowgill, Wolfers, and Zitzewitz 2009). Trading fees are also an option to control for extreme or automated trading activity, but it is thought that these fees distort the market's ability to aggregate participants' information and are not recommended (Chen 2005). Because of the complex nature of valuing, trading, and paying out stock contracts in this type of financial market design, the new non trading market designs mentioned previously have emerged as an attractive alternative.

Participants

Two key dimensions of participation are who and how many traders should participate in the prediction market. For example, a company must decide whether to allow access to the public, to affiliated organizations, or only to employees of their organization (Hopman 2007; Gruca, Berg, and Cipriano 2003; Chen 2005; Cowgill, Wolfers, and Zitzewitz 2009). This is easily achieved through the internet connectivity provided by the market design (Spann and Skiera 2003). The benefit is clearly in the additional and different information that outside parties can bring to the forecast task (Cummings 2004; Grafe, Luckner, and Weinhardt 2010). Affiliated organizations may include suppliers, brokers and agents, customers, and agencies. It is also possible to open markets up to the general public, but this seldom, if ever, done by companies. Confidentiality of business information and outcomes often drives the need for privacy (Spann and Skiera 2003), in these cases, participants are restricted to internal employees only. The flexibility of market designs allows markets to be switched from internal to open markets easily. Whether project insiders and supervisory management participate should also be considered; these people have much more information, have control over outcomes, may be vested in current forecasting process, and may have motivations to bias outcomes toward certain internal goals. There should also be a goal of including people with diverse views and opinions and with access to independent information. As discussed earlier, diversity and access to independent information are critical components behind a crowds' ability to beat analysts and experts (Ho and Chen 2007). A large number of participants is another critical component behind prediction markets' success. Ho and Chen's experience suggests that at least 50 participants are needed for an effective market.

Incentive Program

For a prediction market to be successful there needs to be many participants, frequent trading, revelation of good information, and the desire to perform well (Hopman 2007). The incentive system or program built into a market provides the motivation for these things to happen (Soukhoroukova and Spann 2005). In designing an incentive program, market currency, initial endowments, and market liquidity must be considered.

Market currency is what and how much participants use to trade in the market. Markets can be designed to use real money or virtual money. When virtual money is used, participants redeem their holdings for prizes, raffle tickets (Cowgill, Wolfers, and Zitzewitz 2009), or credits towards merchandise (in the company store for example). At the beginning of the market, participants can invest their own money or be awarded an initial endowment or portfolio to trade with (Cowgill, Wolfers, and Zitzewitz 2009). The initial endowment can be all money, all stocks, or a mix of each (Spann and Skiera 2003). An important consideration for effective markets is that participants desire to perform well because they have something at risk or they have the potential to earn a reward. Therefore, with regard to the amount of currency or rewards, there needs to be a sufficient amount to motivate participation and trading. There must also be limits on currency that can be invested in order to control for market manipulation (Spann and Skiera 2003; Ho and Chen 2007). The IEM allows participants to invest up to $500 of their own money to trade, but companies typically use play money redeemable for merchandise or prizes (Chen 2005). Concerns over legal restrictions on gambling have lead companies and market hosts to adopt play money exchanges (Wolfers and Zitzewitz 2004). The need for active trading is also called market liquidity. To encourage or trigger trading, market designs can have a rule that only participants who trade above a certain minimum level of activity can earn rewards. Initial endowments that are a mix of money and stocks also encourage trading, especially when money and stocks are evenly divided and the stocks are initially evenly distributed across all outcome levels (Ho and Chen 2007).

Market Information

There are two dimensions of information in a prediction market: i) information that is to be provided to participants and made available to participants through market trading, and ii) information revealed through market trading that is used in decision making by managers. Participants need to already have some knowledge about outcomes to inform their behavior or else trades would be random (Spann and Skiera 2003). Ideally they have different levels and types of information as this can support more trading activity (Soukhoroukova and Spann 2005). It is also considered advantageous if there is 'ambiguous' information in the market and if traders disagree about future outcomes. As discussed earlier, this can be achieved through participant diversity (Wolfers and Zitzewitz 2004). Participants can also be given some information at market opening to put everyone on an even baseline and support their trading (Hopman 2007). Information used in the market must also benefit from transparency; information about trades and prices should be posted publicly so that traders can review it, learn, and adjust their behavior accordingly. Past experiments have shown this aspect to be critical to an effectively functioning market (Ho and Chen 2007). Regarding information revealed by the market, participants' final holdings and final market prices will provide information for marketing managers to make decisions, estimates, and plans. The original prediction outcome definition and contract specification determine the nature of the information revealed by the market; as discussed earlier, these might be expected mean values, shares, and distributions.

Integration with Existing Processes

In order for prediction markets to be useful and provide value, their informational outputs need to integrate effectively with the decisions and operations of the organization. This means that market participation and execution need to run in parallel with existing processes and outputs need to be in a form that can be readily used (Hopman 2007). How prediction markets will relate to existing forecasting processes and people should also be considered in advance. Will the market run independently and produce a separate output, or will it be coordinated with existing forecasting processes and be an input to them? This relates directly to the discussion of combining forecasts in the previous forecasting chapter. Ho and Chen (2007) emphasize the importance of the scheduling of markets; they should run sufficiently in advance to allow forecast outputs to influence major decisions and resource allocations.

Prediction Markets and Marketing Forecasting

There have been very few studies performed within a marketing context and no study of prediction markets from a marketing management perspective (marketing's role, key activities, capabilities, and decisions). One area of marketing research employs prediction markets merely as a source of data for the analysis of box-office sales of new movie releases (Wierenga 2006; Elberse 2007). Another area extends prediction markets into the front end of the product development process as a tool to support new product design (Soukhoroukova and Spann 2005; Dahan, Soukhoroukova, and Spann 2009). There are, however, numerous mentions in the reviewed literatures of how marketing learning and deciding can be enhanced by tools and techniques that leverage advances in technology to access and apply collective knowledge from within an organization. Li and Calantone (1998) and Day (2011) argue that market knowledge is not fully usable until it can be transferred from those who have it to those who do not. This is precisely the function that prediction markets can play. Interestingly, Mahajan and Wind (1988) anticipate "development of expert systems for new product forecasting where a user could interact with a system to develop forecasts for a new product based on rules reflecting cumulative industry experience, company experience and other theoretical or empirical findings relevant to the type of product under consideration" (p. 354). In a similar vein, Leonard-Barton (1992) discuss systems, procedures and tools that can tap into the embedded knowledge of project members; Calantone and Di Benedetto (1988) discuss techniques for data gathering, analysis, and decision making; and Slotegraaf and Atuahene-Gima (2011) discuss integration mechanisms that can elevate team information sharing and collaboration.

The introduction discusses the role and importance of new products and programs in business growth. It also discusses marketing's role in influencing, supporting, and managing new initiatives and the need for better forecasting capabilities. A typical process for developing new initiatives generally involves steps such as idea creation and filtering, early concept development, concept evaluation and selection, product development, and planning commercialization (Cooper 1988; Calantone and Di Benedetto 1988). Two of these steps are particularly important to the success of new ventures: concept evaluation and selection and planning commercialization. These are also two areas where marketing plays an important if not the lead role within a firm; picking concepts that will win in the marketplace and forecasting their market demand

(Krishnan and Ulrich 2001). Rao and Bharadwaj (2008) observe that “a decision that marketing managers often must make is to which initiative the firm should allocate its limited resources,” and “a prerequisite to this understanding is knowledge of how the initiative affects the shareholders’ expected cash flows” (p. 19). Mahajan and Wind (1992) discuss how this is also an area where improvement is most needed; they describe the need to add better forecasting models in support of activities including concept screening and business analysis. Ho and Chen (2007) conclude that two ways to improve the success of new ventures is “to invest in only the most promising new product ideas and to improve supply planning before products launch.” They discuss how firms often “fail to correctly pick new product winners” and do not “capitalize on the successes of a new product because of poor demand forecasts” (p. 158).

There are many forecasting methods available to marketing; many are considered traditional and some are considered innovative (see Table 6 in forecasting section). Prediction markets are a forecasting method considered to be an innovative quantitative method. Prediction markets offer marketing the opportunity to have a higher success rate at picking winners in terms of the evaluation and selection of new products and promotions. Prediction markets also offer marketing the opportunity to better forecast demand, specifically more accurate point estimates and reduced variance or error. Ho and Chen (2007) conclude that “a firm can use prediction markets to select the most promising new product ideas and to forecast demand for the selected new products before they are launched. The former use allows a firm to bet on the right product ideas and the latter ensures that the firm can better manage new product launches through better supply planning” (p. 158).

Comparison to Traditional Methods

Forecasting and decision making are often classified as quantitative-data driven or management knowledge-judgment driven (Wierenga, Van Bruggen, and Staelin 1999). Two prominent quantitative-data driven methods are modeling and surveying customers. Prominent management knowledge-judgment driven methods are pooling experts, management meetings, project teams, and hiring consultants (Wolfers and Zitzewitz 2004). There are several issues or problems with these methods. Quantitative-data driven modeling methods suffer from relying on well-structured problems with easily available historic data. Customer surveys often exhibit a weak correlation between customers' stated purchase intentions and customers' actual purchase behavior; it is expensive to identify, contact, and motivate a sufficiently large, representative sample of consumers (Gruca, Berg, and Cipriano 2003); it can take a substantial amount of time to complete a survey (Spann and Skiera 2003); there are often measurement, sampling, and response biases (Gruca, Berg, and Cipriano 2003); most people are imitators and have difficulty expressing their preferences for new products (Spann and Skiera 2003; Ho and Chen 2007); and consumers have no motivation to "reveal their true purchase intentions" (Ho and Chen 2007, 145). In relying on experts, there are often few experts available in a field and they are hard to identify (Spann and Skiera 2003); as a small group there is considerable variance in their forecasts (Ho and Chen 2007); their opinions are not necessarily independent as they may rely on the same information sources (Ho and Chen 2007); they work from past data that may not bear on the future outcomes (Spann and Skiera 2003); and it is difficult to weight their opinions other than equally (Spann and Skiera 2003; Ho and Chen 2007). The forecasts of management or project teams often suffer from organizational, social, or management hierarchical biases. Teams may also be consensus oriented or suffer from group think. For these reasons, information "rolled up through sales, marketing, and business planning teams" for forecasting is often biased or altered in ways that have historically hurt forecast accuracy (Hopman 2007, 127).

There are several characteristics or advantages of prediction markets that address many, if not all of the issues described above. Prediction markets are effective with unstructured problems and where there is no available historic data. Incentives motivate participants to obtain and share information with the market, and compensate them for accuracy (Hopman 2007; Spann and Skiera 2003; Ho and Chen 2007); anonymity removes organizational biases (Hopman 2007); large representative samples are not needed (Gruca, Berg, and Cipriano 2003); multiple judgments reduce variance; diversity introduces opinions and information from different areas (Ho and Chen 2007); the trading mechanism efficiently and accurately aggregates, weights, and averages information from numerous participants (Hopman 2007; Ho and Chen 2007; Berg, Neumann, and Rietz 2009); the internet provides an effective and inexpensive way to collect information from widely dispersed parties (Gruca, Berg, and Cipriano 2003); public trading allows participants to learn from others and update their estimates (Ho and Chen 2007); and, once set up, markets can be repeated or expanded at minimal cost (Spann and Skiera 2003).

A few recent projects in other fields directly link prediction markets and forecasting; this supports the introduction and use of prediction markets in marketing and new products forecasting. This dissertation will build and extend on these studies. For example, Spann and Skiera (2003) make the link between prediction markets and business forecasting. The benefits of prediction markets and the link to business context are discussed and three empirical tests are conducted. Another example is a study by Van Bruggen et al. (2010) into prediction markets as forecasting support systems. They discuss the power of prediction market technology to aggregate diverse public and private information from informants across an organization and convert this into a form that can be used to directly support forecasting. They also demonstrate the positive influence that information heterogeneity has on forecast accuracy. These tests show the potential for the use of prediction markets for business forecasting, however the tests are based on stock trading, movies and sports, small participant pools, and there is no comparison to existing internal forecasts in a realistic business setting. This work provides a good starting point for prediction markets' application in business but a more substantial and ecologically valid test is needed to support conclusions and work towards explaining how results are achieved. Prediction markets offer the advantage providing both point estimates and measures of uncertainty through probability distributions of estimates.

Calls for Research

Armstrong (2006) observes that there is a long history of improving accuracy of estimates by aggregating information from a group of people. He observes that most comparative testing that has been done has been in other domains and there has been little research into understanding prediction markets. Armstrong specifically calls for tests of prediction markets against other structured group methods and for research into how they improve accuracy, under what conditions, how they are best employed. Following from this, Armstrong and colleagues investigate prediction markets relative to some other forecasting methods and identify several conditions that influence when they are appropriate and when and how they perform well (Green, Armstrong, and Graefe 2007; Graefe and Armstrong 2011). In these studies, Armstrong and colleagues discuss (2007) and test (2011) the relative performance of prediction markets compared to some other forecasting methods. On one hand, they note the ability of markets to effectively reveal and aggregate complex, real-world information if there are many participants and a clear known outcome. On the other hand, they raise important issues regarding the effectiveness of markets: complexity due to the price and trading mechanisms, confidentiality, limited direct participant interaction, and the markets' black box nature.

Although prediction markets did not produce significant accuracy advantages compared to the other methods in this study, Armstrong indicates that this may be due to the nature of lab experiments, with students, on non-real world problems. The performance of the prediction markets may also have been influenced by lack of diversity, access to other information, basic knowledge, and experience; low numbers of participants; and low levels of incentives. Encouraged by the results of their prediction market tests on forecasting, Spann and Skiera (2003) call for further field research into the impact of design factors in more realistic business forecasting settings and with alternative market designs. In response to these calls, the purpose of this dissertation is to further examine and test these issues to contribute to the assessment of prediction markets' performance and their suitability to marketing forecasting applications. Before prediction markets can be considered as a new methodology, their efficacy must be demonstrated in marketing and their mechanism explained.

This raises two fundamental questions I propose to investigate:

1. Can prediction markets improve forecast accuracy in marketing applications?

2. How do prediction markets improve marketing forecast accuracy?

CHAPTER 3

THEORETICAL FRAMEWORK AND HYPOTHESES

As has been described, there is an opportunity to take advantage of advances in collective intelligence to improve marketing forecasting in new product development and other important areas. This chapter proposes a framework for analyzing how electronic prediction markets (EPMs) may employ unique factors from collective intelligence and established factors from market knowledge (marketing information processing) to improve forecasting outcomes. Figure 1 presents these factors and their relationships to outcomes and will support investigation into the two research questions. The framework in Figure 1 incorporates the market knowledge factors of acquisition, interpretation, and dissemination as independent variables; the collective intelligence factors of diversity, independence, and incentives, and information aggregation as independent variables; and prediction market forecast accuracy as the final outcome and dependent variable. The market knowledge and collective intelligence factors will be shown to address several of the new products, capabilities, and market knowledge improvements called for in the literature review chapters. Each of these factors and their relationships are described, and corresponding hypotheses developed, in the following sections.

West (1994) identifies six dimensions for evaluating forecasting methodologies: accuracy, reduced costs, speed, ease of understanding and use, credibility, and data requirements.

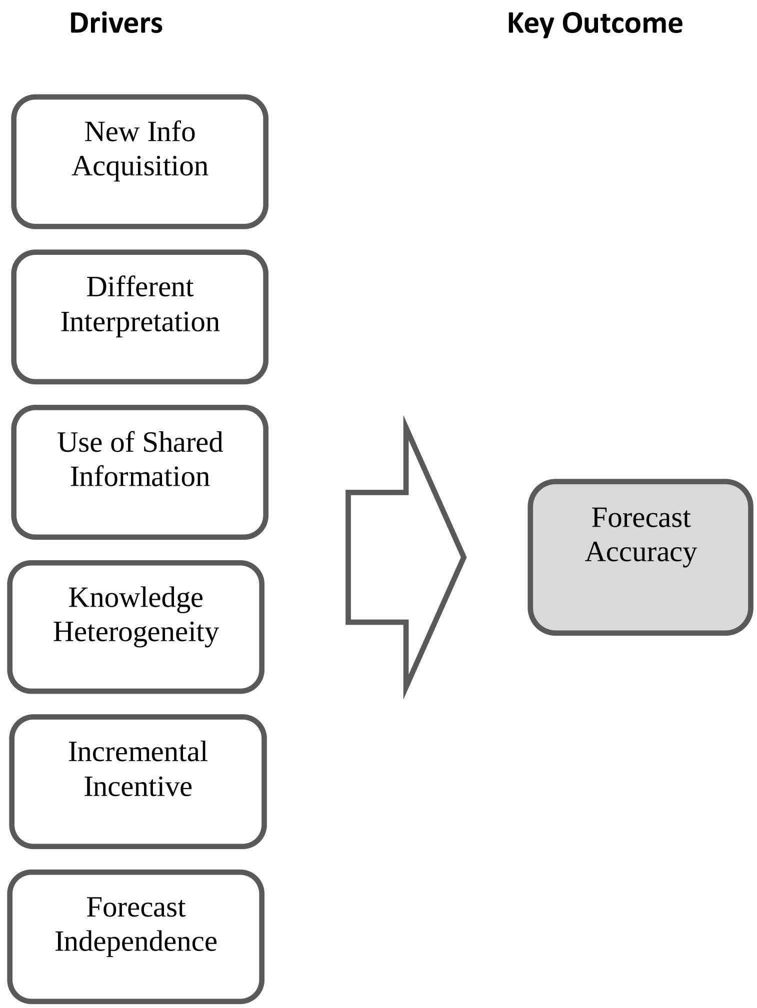

Figure 1. Conceptual Framework for Prediction Markets Forecasting

Performance is the primary requirement for prediction markets to be considered as advancement in marketing forecasting methodology, specifically more accurate point estimates and reduced variance or error. Therefore, accuracy will be studied in first in this dissertation.. If prediction markets provide sufficient accuracy improvements over traditional methods in predicting future outcomes, then the reasons why they perform well will be studied. Based on this, hypothesis one addresses prediction accuracy and will be tested in Study I.

H1: The aggregate forecasts of prediction markets are more accurate than forecasts produced by the traditional methods used within major firms.

If prediction markets are shown to improve marketing forecasting, the next most important research question will be how do they achieve their results; what is the mechanism that produces improved forecasting outcomes? This will answer research question two and be tested in Study II.

Market Knowledge Factors

Within the new products and capabilities literature reviewed in this dissertation, market knowledge and decision making are identified as key dimensions and as areas where improvements and innovations can enhance new product and marketing outcomes. Within the decision making literature, market knowledge is a key input and component linked to effective decision outcomes. Within the market knowledge literature, the marketing information processing elements of information acquisition, interpretation, and dissemination are consistently shown to be key dimensions that produce market knowledge. For example, Li and Calantone (1998) describe the role and importance of market knowledge competence within new product development and describe the customer knowledge process as comprising acquisition, interpretation, and integration of market information. Because these represent action individuals do or do not take, they can also be considered as behavioral factors (Kirca, Jayachandran, and Bearden 2005; Day 1994). Market knowledge is used to make marketing forecasts that are inputs into marketing decisions in areas such as new products, marketing, and operations (e.g. supply chain). Therefore, a model that proposes a new methodology to improve marketing forecasting outcomes should incorporate and leverage the marketing information processing factors described. In the prediction markets forecasting model proposed in Figure 1, acquisition, interpretation, and dissemination and their impact on forecast accuracy will defined in the following ways.

New Information Acquisition

In the market knowledge chapter, acquisition is identified as the first of three marketing information processing factors that produce market knowledge. For the purpose of modeling how prediction markets work, new information acquisition will be defined as participants searching for and obtaining additional or different information to use in their individual predictions. This can be new, local, or specialized data, observations, and analysis from within and outside of the organization. From the marketing literature, Moorman (1995) describes acquisition as “bringing information about the external environment into the boundary of the organization” (p. 320). Sinkula et al. (1997) describe “information generation [as] the process by which information is collected” (p. 308). Slater and Narver (1995) describe learning organizations as basing their knowledge on “experience, experimentation, and information from customers, suppliers, competitors, and other sources” (p. 71). They find information may come from direct experience, others’ experiences, or organizational memory. Regarding new products, Kahn (2002) emphasizes the importance of personal data in new product forecast accuracy and Brown and Eisenhardt (1995) emphasize the importance of external communication for increasing the amount and variety of information in higher performing development processes. Managers in effective learning organizations have multiple internal and external sources of information and search beyond formal internal information systems. Huber (1991) describes organizational information acquisition as occurring in three ways: scanning, focused search, and performance monitoring. Scanning is focused on wide ranging sensing of the external environment, focused search is organizational members actively searching for information related to a specific problem or opportunity, and performance monitoring is assessing the organization's achievement of goals and plans. Slater and Narver (2000) identify four forms of information acquisition or intelligence generation: market-focused or scanning, collaborative relationships, experimentation, and repeated experiences. They find through an empirical study that effective intelligence generation practices are positively associated with product quality, new product success, customer satisfaction, and sales growth. Sinkula (1994) and Van Bruggen et al. (2010) propose that market information in decentralized organizations is often difficult to access, and if new knowledge is going to benefit the organization, it must move from the creator to organizational use. Therefore, a more active (vs. passive) information acquisition orientation has a bearing on organizational learning. The value of new acquired information is stressed as Day (2011) observes that marketing needs to be able to bring insights within the organization to the surface and be able to translate data into useable form:

> An open system allows for information flow across previously hard boundaries within and outside a firm. Expertise can emerge from myriad sources. If channeled or monitored effectively, these can offer tremendous power and insight to an organization. Through a web of partners and collaborators, an open network provides access to a deeper set of resources and specialized skill sets than a closed model. (p. 190)

In the diversity literature, Jackson and colleagues find that acquisition of knowledge, seeking and receiving work-related information, and searching more broadly for information can improve team decision making (Jackson, May, Whitney 1995; Jackson and Joshi 2011). March (1991) and Kim and Atuahene-Gima (2010) relate new information acquisition to exploratory activities that introduce new information and increase the aggregate knowledge of the organization. March (1991) specifies that is not the amount of knowledge that organizational members already possess that produces better performance, it is the new knowledge they bring. It is proposed that when market participants bring additional or different information to the prediction market, this new information can be used in their private deliberations and predictions, and adds new information value to the ultimate market prediction.

H2: If there is increased new information acquisition, then there will be greater accuracy of the aggregate prediction market forecast.

Differences in Interpretation

Interpretation is identified in the market knowledge chapter as the second of three marketing information processing factors that produce market knowledge. For the purpose of modeling how prediction markets work, differences in interpretation will be defined as participants actually using or employing different information and thinking to make their individual predictions. Difference in thinking could pertain to using different perspectives, knowledge, experiences, skills, and abilities. This could also involve using a different approach, process, or analysis to arrive at their final prediction. This might also involve different interpretations of existing information. Huber (1991) describes this directly, “It seems reasonable to conclude that more learning has occurred when more and more varied interpretations have been developed, because such development changes the range of the organization's potential behaviors, and this is congruent with the definition of learning” (p. 90).

From the diversity literature, Page (2007) argues that after a basic ability level is met, people having different perspectives, different interpretations of information, and following different approaches to solving problems is more important than higher levels of ability. Jackson and colleagues observe that differences in consolidation of task-based information, information processing, patterns of task-based cognitions, all help consider alternative solutions and improve team decision making (Jackson, May, and Whitney 1995; Jackson and Joshi 2011).

These descriptions of interpretation align with Moorman (1995) and Day’s (1994) emphasize on utilization as an important component of market learning capability. Moorman (1995) describes instrumental utilization as “the extent to which an organization directly applies marketing information to influence strategy-related action” (p. 320). She further describes this as the use of information in making, implementing, and evaluating marketing decisions. Sinkula et al. (1997) describe “information interpretation [as] the process which information is given one or more commonly understood meanings…managers employ mental models to interpret information” (p. 308). Slater and Narver (1995) describe for learning organizations “through complex communication, coordination, and conflict resolution processes, these organizations reach a shared interpretation of the information, which enables them to act swiftly and decisively to exploit opportunities and defuse problems" (p. 71). They also emphasize the importance of "exposing new information to multiple interpretations using programmed techniques" (p. 65). In describing the wisdom of crowds, Surowiecki (2005) discusses how people are able to specialize and draw on local knowledge in their interpretation and analysis.

> Collective decisions are most likely to be good ones when they're made by people with diverse opinions reaching independent conclusions relying primarily on the private information…Tacit knowledge is knowledge that can't be easily summarized or conveyed to others, because it is specific to a particular place or job or experience, but it is none the less tremendously valuable. The virtues of specialization and local knowledge often outweigh managerial expertise in decision making. (p. 10)

Day (2011) describes how "a vigilant leadership team nurtures a supportive climate for gathering, sharing, and acting on information from diverse sources… These leaders tend to be more open, seek diverse inputs, and foster wide-ranging social and professional networks" (p. 191). The value of differences in interpretation is also discussed in the new products and forecasting literature. Brown and Eisenhardt (1995) discuss the value of varying interpretations, even of the same information from individuals from different departments. Marsh and Stock (2006) acknowledge the implications for new product development from how well knowledge is interpreted (sorted, categorized, and given meaning). Armstrong (2001c) describes this regarding forecasting, "The more that data and methods differ, the greater the expected improvement in accuracy over the average of the individual forecasts" (p. 2). And Armstrong (2001b) advises forecasters to combine forecasts from approaches that differ to improve forecast accuracy. It is proposed that when participants use different information and thinking in their predictions, prediction outcomes are improved.

H3: If there is increased differences in interpretation, then there will be greater accuracy of the aggregate prediction market forecast.

Use of Shared Information

The dissemination of information is identified in the market knowledge chapter as the third of three marketing information processing factors that produce market knowledge. The prediction market technology platform provides two forms of information; the first is background information that establishes a minimum common information baseline for all participants. The second is the ability for participants to view combined predictions made by other participants in real time. For the purpose of modeling how prediction markets work, dissemination will be defined as participants using the information shared in the system to make and update their predictions.

In the marketing literature, Moorman (1995) describes dissemination as formal and informal transmission processes that diffuse information to users within the organization. Sinkula et al. (1997) describe “information dissemination [as] the process which information is shared and diffused horizontally and vertically throughout the organization” (p. 308). Maltz and Kohli (1996) discuss how “market intelligence use may be improved by designing appropriate dissemination processes” (p. 48).

In the prediction markets literature, publicly viewable prices or predictions provide feedback on the most recent information available to the market, which allows participants to learn from others, update their own information, and update their estimates (Hopman 2007; Ho and Chen 2007). The viewable predictions act as price formation mechanisms do in market exchanges; they allow for the efficient and accurate aggregation and weighting of information that is normally a cumbersome and complex task (Berg and Rietz 2003; Wolfers and Zitzewitz 2004). The fact that trading activity is publicly viewable by all participants allows for instantaneous updating of market information (Spann and Skiera 2003). Market mechanisms share collective information which transfers private information from knowledgeable informants to less knowledgeable informants; less informed participants learn from more informed and markets are smarter overall (Ho and Chen 2007; Van Bruggen et al. 2010). Based on this, the following hypothesis will used to test the impact of dissemination on final prediction outcomes.

H4: If there is increased use of shared information, then there will be greater accuracy of the aggregate prediction market forecast.

Collective Intelligence Factors

In the collective intelligence and prediction markets literature, diversity, incentives, anonymity, and information aggregation are identified as key dimensions and drivers of the prediction markets mechanism that produces greater forecast accuracy. These concepts are identified and developed throughout the literatures of a very diverse field of disciplines and are proposed to have consistently described effects on information outcomes. These effects are not, however, specifically tested empirically in any of the literatures. Therefore, a model that proposes to explain how prediction markets produce their results should incorporate and leverage the collective intelligence factors described. In the prediction markets model proposed for the present study (see Figure 1), diversity, incentives, anonymity, and information aggregation and their impact on forecast accuracy will defined in the following ways. Because these represent conditions or influences of the organization in many ways, they can also be considered as cultural factors (Kirca, Jayachandran, and Bearden 2005; Day 1994; Bharadwaj, Nevin, and Wallman 2012).

Knowledge Heterogeneity

Diversity is identified in the prediction markets chapter as a collective intelligence factor widely credited with the superior performance of prediction markets. More detailed analyses, however, distinguish that it is the differences in information, knowledge, and opinions that diversity brings to the market that actually produces prediction markets' superior performance. This is an important distinction. For the purpose of modeling how prediction markets work, knowledge heterogeneity will be defined as participants having different perspectives, information, experiences, skills, and abilities to bring to a prediction as a result of being different from each other (Milliken and Martins 1996; Van Der Vegt and Janssen 2001; Page 2007). The next paragraphs will describe diversity within organizations, the resulting knowledge heterogeneity, and how they relate to new product processes and forecasting.

Diversity can be considered as the primary source of knowledge heterogeneity. Jackson and colleagues define diversity as the extent to which members of social units are dissimilar from each other, on one or more attributes, based the social composition of work teams (Jackson and Joshi 2011; Jackson 1996; Jackson, May, and Whitney 1995). They make the distinction that diversity is a characteristic of a group not an individual. Jackson and Joshi (2011) break aspects of diversity into readily detectable versus underlying attributes. In terms of work, readily detectable or observable differences include tenure, department membership, network membership, industry experience, formal credentials, and education level. Underlying or unobservable differences include task related knowledge, skills, abilities (cognitive), experience, and task related information. Having diversity brings several benefits to a marketing decision: it brings different perspectives (Page 2007; Milliken and Martins 1996; Surowiecki 2005); it can reduce the negative effects of group interactions such as groupthink or dominant ideology (Surowiecki 2005; Hurley and Hult 1998); and it can increase the cognitive resources available to a task (Jackson and Joshi 2011).

Knowledge heterogeneity is developed in the marketing, new products, and organizational learning literatures. Day (2011) notes the importance to new product success of heterogeneous knowledge. He discusses how adaptive firms recognize the value of diversity, work to bring together different perspectives, act on information from diverse sources. He states, "The first step to increasing adaptability is to diversify the talent pool with people that are not wedded to old and unquestioned assumptions. Outsiders or closely connected partners such as advertising agencies bring different life experiences and an openness to divergent information" (p.191). Kim and Atuahene-Gima (2010) describe how exploratory market learning introduces new knowledge from outside the organization and exposes the firm to new and heterogeneous information that departs from the firm's existing skills, knowledge, and experiences. Similarly, Slotegraaf and Atuahene-Gima (2011) find that the heterogeneous knowledge shared within cross-functional new product teams based on distinct expertise and knowledge can be of great importance new product success. More generally, Sinkula (1994) describes how more people involved in processing contrary information leads to enhanced organizational learning. Huber (1991) describes how “more organizational learning occurs when more and more varied interpretations are developed, because such development changes the range of potential behaviors” (p. 90). He also describes how cognitive maps influence interpretation of information people have and how the maps or mental frames of reference differ across organizational units. To avoid learning traps, Slater and Narver (1995) note how managers in learning organizations rely on networks that include people with different perspectives. March (1991) describes how heterogeneity in learning produces non-redundant information that increases the knowledge of the organization.

In the prediction markets literature, Van Bruggen et al. (2010) find that heterogeneity in market knowledge increases forecasting accuracy as people at different hierarchical levels, in different departments, and in different geographical areas will know more and access more information. They define information-heterogeneity as “the variations in knowledge, know-how, information and expertise which a group of forecasters can tap” (p. 407). Ho and Chen (2007) observe that participant diversity introduces diverse views and opinions and new information from different people and areas. When aggregating information, diverse views and opinions produce complementary bits of truth while independent errors and biases cancel each other out (Servan-Schreiber 2012). Page (2007) observes that diversity improves collective performance at predictions because averaging multiple personal predictions will be more accurate than the predictions of even the best people. It is proposed that when multiple market participants have different knowledge and opinions to bring to the prediction market, their combined predictions will be better.

H5: If there is increased knowledge heterogeneity, then there will be greater accuracy of the aggregate prediction market forecast.

Forecast Independence

Independence or autonomy is another collective intelligence factor identified in the prediction markets chapter and referenced throughout the literature of the various fields. Independence results from providing anonymity to participants and allowing them to use their own information sources, follow their own individual processes, and express their opinions freely. For the purpose of modeling how prediction markets work, forecast independence will be defined as participants being willing and able to share individual information and opinions in their predictions because they are free from organizational influence and consequences and they can chose their own sources and approach.

In the prediction markets literature, independence facilitates the sharing of expertise and innovation (Hurley and Hult 1998) and challenges the status quo (Page 2007). Anonymity of the market protects participants from the political or social consequences of disclosing true beliefs and removes organizational biases (Hopman 2007). Wolfers and Zitzewitz (2004) describe this free flow of information as 'truthful revelation'. Social consequences often produce significant biases in traditional estimation and forecasting processes within organizations (Berg, Neumann, and Rietz 2009; Cowgill, Wolfers, and Zitzewitz 2009). Ho and Chen (2007) discuss how prediction markets benefit from "the free flow of independent information" (p. 152) because organizational barriers are removed. Berg and Rietz (2003) describe anonymity afforded to market participants as important for producing unbiased forecasts. Independence also allows for a decentralized process that removes the constraints of methods and sources when determined in a top down manner. This also allows participants to draw from local and specialized information (Surowiecki 2005). Surowiecki notes that when there is independence, participants' opinions are not determined by the opinions of those around them, that they are free from the influence of others.

In the marketing literature, Day (2011) discusses how marketing needs to be able to "overcome organizational filters" and defend against "individual and organizational biases that inhibit real insight" (p. 188). He discusses how management systems influence the ways that knowledge is created and controlled, they "dictate what information is to be collected, what types are most important, who gets access to the information, how it is to be used" (p. 39). Sinkula (1994) describes how politics, norms, and assumptions influence how information is acquired, distributed, and even interpreted. Sinkula et al. (1997) describe barriers to organizational learning such as censoring used to maintain a positive organizational environment or avoid conflict with managers' mental models. In the forecasting literature, the importance of ensuring independence from client pressures, organizational factors, and politics is described as necessary to minimize biases that can ultimately diminish forecast accuracy (Ehrman and Shugan 1995; Armstrong 2001d; Fildes and Hastings 1994; Armstrong 2001a). It is proposed that if they are free from organizational influence and consequences and can chose their own sources and approach, participants will be willing and able to share individual information and opinions in their predictions.

H6: If there is increased forecast independence, then there will be greater accuracy of the aggregate prediction market forecast.

Incremental Incentive

Incentives are also identified in the prediction markets chapter as a collective intelligence factor referenced throughout the literature of the various fields. Incentives motivate individuals to bring new information to the prediction market, share their opinions, and to put effort into making accurate predictions. For the purpose of modeling how prediction markets work, incremental incentive will be defined as extrinsic and intrinsic rewards that provide motivation for participants to invest time and effort into searching for information and making accurate predictions. Extrinsic rewards are typically money and prizes, but intrinsic rewards could include recognition or respect of peers, task challenge, sense of accomplishment, and feeling of a worthwhile accomplishment (Abbey and Dickson 1983; Ingram and Bellenger 1983; Chiang and Birtch 2005).

Osterloh and Frey (2000) indicate that "motivation is not a goal in itself but should serve to support a firm's goals…employees must be motivated to perform in a goal oriented way" (p. 540). They also make important distinctions between tacit and explicit knowledge and between intrinsic and extrinsic motivation. Explicit knowledge is more tangible; it is "transferable and appropriable" but is a small part of individuals' actual knowledge. Tacit knowledge is less tangible, it is created and kept within individuals and cannot be transferred or traded. Tacit knowledge is more valuable as a non-imitable resource. Extrinsically motivated employees are suited to monetary pay for performance incentives which they can use to satisfy their needs. Intrinsically motivated employees derive satisfaction directly from their activity or task. They are motivated by non-monetary incentives. Balancing extrinsic and intrinsic incentives is important. Explicit knowledge is easier to monitor and can be compensated with extrinsic rewards, but tacit knowledge must normally be rewarded with intrinsic rewards. Osterloh and Frey (2000) argue that "knowledge transfer is intimately connected to motivation and that sustainable competitive advantage requires a corresponding motivation management." (p. 538). Jenkins et al. (1998) perform a meta-analysis of empirical research into financial incentives and performance effects. They find that "financial incentives also convey symbolic meaning (e.g. recognition, status) beyond their monetary value" (p. 777). They indicate that "financial incentives also supplement intrinsic rewards". Results support that incentives are related to performance and are explained by expectancy, reinforcement, and goal-setting theories.

In the forecasting literature, Gartner and Thomas (1993) find that payoffs for more accurate forecasts led to increased accuracy. In the prediction markets literature, incentives are described as motivating participants to gather, create, and share information with the market, and compensate them for accuracy (Spann and Skiera 2003; Hopman 2007; Ho and Chen 2007; Berg, Neumann, and Rietz 2009). Wolfers and Zitzewitz (2006) describe how incentives motivate 'information discovery'. These same incentives motivate participants to perform well in their estimates of future outcomes and associated market activities (Hopman 2007; Ho and Chen 2007). Surowiecki (2005) explains that "people focus better on a decision when there are financial awards attached to it…status and reputation provide incentive enough to encourage a serious investment of time and energy …companies should be looking for ways to provide their employees with the incentives to uncover and act on private information" (p. 20). It is proposed that the extrinsic and intrinsic rewards built into a prediction market will motivate participants to invest time and effort into searching for and obtaining additional information, sharing their information and opinions, and trying to be as accurate as possible.

H7: If there is incremental incentive, then there will be greater accuracy of the aggregate prediction market forecast.

Information Aggregation

One of the most important parts of prediction markets' mechanism is their ability to handle the complex task of aggregating information. This is achieved by collecting widely dispersed information and interpretations from participants, focusing them on a specific marketing question and having them predict a single common metric. Technology platforms provide participants with continuous access to the market, collect all of their individual level predictions in a central place, and aggregate their predictions into a single distribution of data with indications of central tendency and variance. For the purpose of modeling how prediction markets work, information aggregation will be defined as the real time, continuous collection and combining of multiple individual predictions and confidence levels, through a central interactive technology platform. In this way, prediction markets may serve as a lens through which market information is interpreted (Sinkula 1994) and as a bridge between individual and organizational levels of information processing and use (Moorman 1995). Prediction markets' collection of participants' predictions provides a unique form of what Slater and Narver (1995) refer to as "shared organizational interpretation of the information" and "information technology…to provide forums for information exchange and discussion" (p. 65). In this way, prediction markets can be viewed as employing the market information processing functions of acquisition, interpretation, and dissemination in a uniquely adapted way, applied to a specific task.

From the prediction markets literature, the market mechanism efficiently and accurately aggregates, weights, and averages information from numerous participants (Hopman 2007; Ho and Chen 2007; Berg, Neumann, and Rietz 2009). The price formation mechanism of the exchange allows for the efficient and accurate aggregation and weighting of information that is normally a cumbersome and complex task (Berg and Rietz 2003; Wolfers and Zitzewitz 2004). Even though participants have different levels of information accuracy, Ho and Chen (2007) observe that “the use of price forces participants to express their thinking in a precise and common metric” (p. 151). The single central value of the distribution of collective predictions serves the same role as the price mechanism in a trading market. Surowiecki (2005) stresses that a decentralized process can only produce results if there is a means of aggregating the information of everyone in the system. He emphasizes that the success of markets are not based on the performance of the smartest people in the group, but rather the combination of everyone’s predictions. Having a large number of participants making predictions drives the efficacy of aggregation in prediction markets. Surowiecki (2005) in describing the wisdom of crowds, describes how a large group of non-experts can beat a small number of experts at a prediction task. This observation is grounded in the statistical principle of the Law of Large Numbers (Ho and Chen 2007). According to this this law, as the size of a sample increases its mean converges to the population mean (Blume and Royall 2003; Sedlmeier and Gigerenzer 1997). In the case of prediction markets, as the number of participants increases, their aggregated predictions move closer to actual values of the outcomes.

Prediction markets in practice have included up to 3,000 participants, but markets with as few as 30 participants have shown strong results (Servan-Schreiber 2012).

In the forecasting literature, the concept of aggregation is addressed through combining forecasts. For example, Batchelor and Dua (1995) find that combining forecasts from different methods is best for improving accuracy because errors made by individual forecasts are least correlated. In the new products literature, aggregation is addressed as information integration, especially with regard to cross functional teams and external network partners (Brown and Eisenhardt 1995; Marsh and Stock 2006; Slotegraaf and Atuahene-Gima 2011).

Information aggregation in this analysis does not lend itself to a relational proposition; it is considered solely as an enabling or instrumental factor. It has binary character or condition: it is present and the prediction market exists and functions and other effects are possible or it is not present, no prediction market exists and there are no other factors or outcomes possible. It is a critical and rather unique function of the prediction market system. In this model it exists, integration and aggregation occur, and the other factors are present to exhibit their propose effects. This is described further in the treatment and control discussion of the research design section in the methodology chapter for Study II. Therefore, information aggregation is indicated in Figure 1, but there is not a hypothesis or test designed into this study.

CHAPTER 4

STUDY I METHODOLOGY AND RESULTS

As part of an academic-practitioner research collaboration, an actual electronic prediction market (EPM) was designed and implemented within a Fortune 100 company that is also a Marketing Science Institute member. Lumenogic, a consulting firm and recognized leader in collective intelligence applications was engaged to design and host the prediction market's technology platform. Theory and specifications from the prediction markets literature, used to develop the research hypotheses, drove the design of the prediction market. The prediction market ran within three autonomous operating divisions within the subject company.

Study I compares prediction market outcomes and existing internal company forecasts to actual outcomes to assess the relative performance of prediction markets. This will help determine whether markets can improve forecasting and decision outcomes. Study II designs and implements a cross sectional post survey of market participants. This, combined with prediction market data, is used to test the series of hypotheses that attempt to explain the prediction market mechanism that improves accuracy. The following sections describe the collaborating companies, the prediction market design, participants, data to be used in the comparative analysis, and final analyses.

Participants and Market Design

Collaborating Companies

In order to provide as much generalizability as possible, the prediction market was implemented within three autonomous operating divisions of the U.S. operations of a consumer packaged goods food company. It is a publically traded, mature company, operating in a very well developed industry. Each division operates in a different product category and has a separate executive team, marketing function, research team, and forecasting team. One division is a business-to-business (B2B) foodservice producer, another is a consumer packaged goods prepared foods producer, and the third is a consumer packaged goods beverage bottler. A test of prediction markets should compare prediction market outcomes against a traditional forecasting method, applied simultaneously, on the same forecasting task. This should be implemented within a company that has much at stake with the success of new initiatives and has a routine of developing new products and programs. Having much at stake makes the outcomes of forecasting important to the organization and ensures sufficient effort and care is normally applied against traditional forecast methodologies. A history of developing new products and programs controls, to some degree, for maturity factors in the new product development process. Conducting the test in a consumer packaged goods company is representative of the challenges and risks associated with picking winners and estimating demand that traditional forecasting methodologies face.

In order to economize on cost and time, and to focus primarily on the performance of prediction markets, it was decided to host the market through an expert collective intelligence firm that has already solved the design problem and has experience developing and managing prediction markets and technology platforms. This also taps into the value consultants, as intermediaries, can bring to a research collaboration as highlighted in the best practices of ISMS-MSI Practice Prize Finalists (Lilien, Roberts, and Shankar 2011). The prediction markets literature identifies several firms that have performed this work. Upon reviewing these firms, one was selected that has extensive experience hosting prediction markets, custom designing markets, and developing innovative trading systems. It was also necessary that the firm be willing to work with design and methodological requirements stemming from the review of the literature and theory. Lumenogic (formerly NewsFutures) was mentioned several times in research and industry articles in conjunction with successful prediction market applications. This firm was selected and contacted and an agreement was reached to support the research project.

There are several common design parameters and requirements discussed in the prediction markets literature that guided the design of this prediction market implementation: technology interface, predicted outcomes, question specification, participants, incentive program, and shared market information. Design decisions and details outlined below are based on those facets that received the most favorable assessments in the review of prediction market studies in the literature review.

Participants

Two key dimensions of participants are who and how many people should participate in the prediction market. For example, a company must decide whether to allow access to the public, to affiliated organizations, or only to employees of their organization (Hopman 2007; Gruca, Berg, and Cipriano 2003). Affiliated organizations may include suppliers, brokers and agents, and agencies. On one hand, opening up a market to outside organizations can bring in new and different information, perspectives, and experiences to apply to the solving the forecasting problem (Cummings 2004). This aligns with Day's (2011) argument for an open marketing organization that leverages resources dispersed across a firm and its network partners. On the other hand, confidentiality of business information and outcomes often drives the need for privacy and internal markets (Spann and Skiera 2003). This issue drove the decision for the present study to use an internal market. For this study employees from each of the three operating divisions were recruited to the prediction markets for a total of 529 invited participants. No outside parties were invited to participate. From a combination of the company directory and payroll records, research directors from each operating division generated a comprehensive list of participants from various functions and job levels to be recruited including marketing, sales, finance, supply chain, market research, human resources, and research and development (R&D). Management level corporate division staff were also included in this sample frame.

Table 7 indicates the breakdown of employees who were recruited from within the company, by operating division. Participants were required to be part of the corporate office, full time, professional staff so that they have basic knowledge of the operating division and its products, markets and business. No hourly or front line field staff were recruited due to their potentially limited understanding of the larger business. The number of invitees per SBU is reflective of the relative size of the SBUs.

Table 7. EPM Participant Sample Frame

	SBU 1	SBU 2	SBU 3
Recruited Participants	104	120	305

A convenience sample of participants was recruited through an announcement letter from their management. This letter directed them to the EPM website and technology platform where they registered and received orientation and instructions Incentives and anonymity were also explained at this point. The implementation procedures and schedule of contact and recruitment activities for the EPM were designed according to the tailored design method (Dillman Smyth, and Christian 2009) to maximize market participation level and quality. The number and timing of contacts were carefully programed and executed to achieve these goals; as were the format, content, and style of communications; the sources of communications; and the number and nature of the inducements. Table 8 demonstrates how these were actually executed and Appendix A shares sample communications. For example, based on the advice of Dillman and colleagues, contacts were personalized, there were multiple strategically timed contacts, contact messages were varied, contacts were brief, and subject lines were carefully written. In addition, to establish trust, high level sponsorship was used, the importance of the task was emphasized, and confidentiality was assured. To increase benefits of participation, the survey was explained, help was asked for, thank yous were made, tangible rewards were offered, the task was made interesting, and exclusivity of participation was established. Finally, to decrease personal costs of participation, ease of access and shortness of survey was demonstrated, no request for personal information was established, and the task was described as routine.

Of the 529 invited employees, 207 employees registered in the EPM system and 154 of those made at least one prediction. Tables 9 through 11 show a breakdown of participation by function, SBU/division, and employment tenure. From these tables, it can be seen that almost 70% of participation came from R&D, Marketing, and Supply Chain. The distribution of participants across SBUs is commensurate with the relative sizes of the SBUs. Most participation came from employees with 10 years or less experience at the company.

Technology Interface

The technology interface provides participants with a way to interface with the market and other participants (Hopman 2007). One key area of criticism of prediction markets has been the lack of knowledge average people have about stock market trading, the difficulty they have participating in stock markets, and the negative effect this has on the level and quality of participation. This has been especially true for prediction markets implemented within companies (Servan-Schreiber 2012). In response to this, leading prediction market providers have been developing and experimenting with markets that are not based on stock market trading systems. Tests show that these markets are much easier for participants to use, their aggregation is as effective as the price mechanism, and their results are equally as accurate (Servan-Schreiber 2012). For these reasons, a new non-trading design, competitive forecasting, was selected and implemented for this study. With competitive forecasting, multiple participants privately indicate their predictions about future outcomes (e.g. projected sales increase) on interactive continuous scales hosted within the technology platform. Participants can view market background information available to all participants and then make predictions. After they make their predictions, they are able to view the combined predictions of all participants and update their own prediction. They can return an unlimited number of times to view real time market results and update their own predictions. The combined competitive forecasts, presented as a distribution of forecasts with a central value, serve the same role as a stock price in a trading based system.

A senior research executive within the subject company sent an email to predetermined participants with a weblink to the technology platform hosted on Lumenogic's server. The first time they entered the system, participants registered with a private username and password which they used each time they reentered the market. They could log in from any computer with internet connection, 24 hours each day and seven days in the week. During their first log in, participants were introduced to a 10 minute training video that provided orientation to the market, how to make predictions, and how to access static supporting information and collective predictions within each prediction question. Figure 2 shows an example of the online interface that participants would interact with for any of the questions that they are forecasting.

Table 8. EPM Recruitment Procedures

Purpose/Source	Timing	Format	Audience	Content
Wave 1 Announcement /SBU Research Directors	8/11/11	Formal email	Full SBU samples	Introduce and describe EPM Explain benefits Announce rewards Share link to EPM system
Wave 2 Reminder /SBU Research Directors	8/17/11	Informal email	Full SBU samples	Reminder for participation Update on registrant count so far Thank you for support
Wave 3 Challenge /SBU Research Directors	8/29/11	Informal email	Full SBU samples	Share participation rates across SBUs Challenge to improve SBU rate Encouragement to view results within EPM
Wave 4 Update /SBU Research Directors	9/15/11	Informal email	Full SBU samples	Share participation rates across SBUs Share time remaining Highlight rewards available
Wave 6 Reminder /SBU Research Directors	9/23/11	Informal email	Full SBU samples	Time is running out warning Update on SBU participation rate improvements Share positive feedback from actual participants
Wave 6 Final Reminder /VP Research	9/27/11	Formal email	Full SBU samples	Last chance to participate Importance of innovative pilot Exclusivity of invitation list and value of participating Describe EPM and benefits Share example of prediction results Highlight rewards available
Wave 7 Final Reminder /SBU Research Directors	9/30/11	Informal email	Full SBU samples	Last chance to participate Highlight rewards available Thank you for participating

Table 9. EPM Participation by Function

Function	Frequency	Valid Percent
R&D	48	31.2
Marketing	34	22.1
Supply Chain	26	16.9
Sales	15	9.7
Insights	14	9.1
Fin	9	5.8
Other	7	4.5
HR	1	0.6
Total	154	100.0

Table 10. EPM Participation by SBU/Division

SBU/Division	Frequency	Valid Percent
SBU2	74	48.1
SBU1	35	22.7
SBU3	24	15.6
Corp	11	7.1
Other	10	6.5
Total	154	100.0

Table 11. EPM Participation by Tenure

Years Employment	Frequency	Valid Percent
0_2	38	24.7
3_5	41	26.6
6_10	43	27.9
11_20	22	14.3
21_on	10	6.5
Total	154	100.0

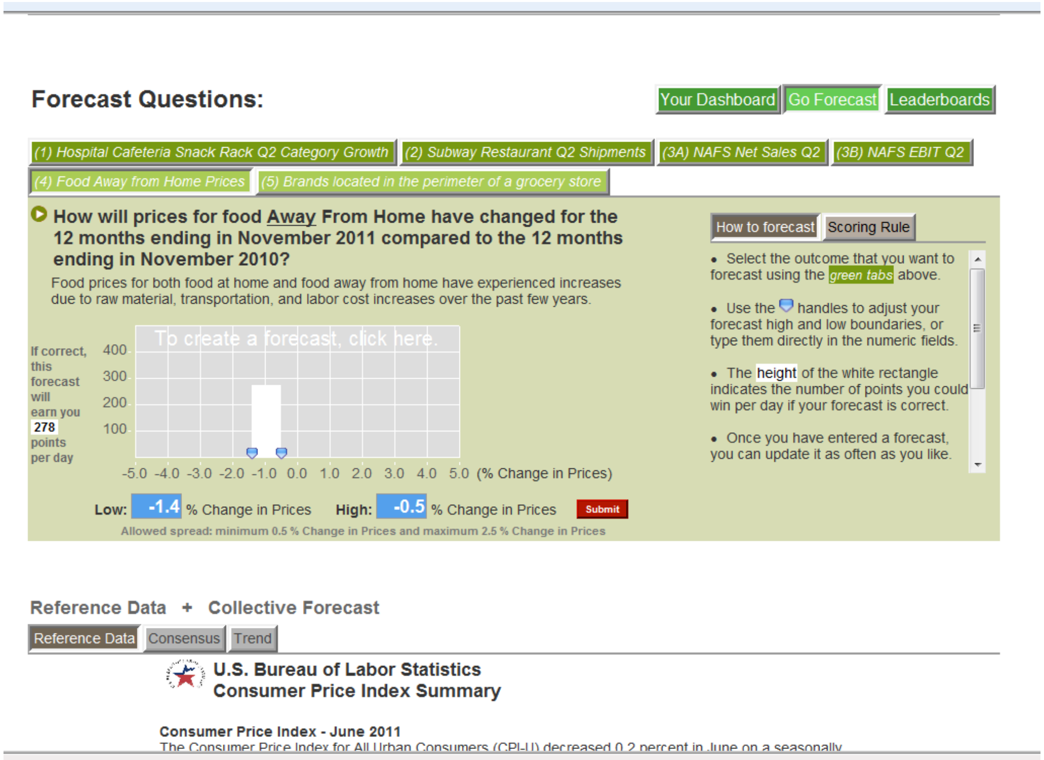

Figure 2. Image of EPM Technology Interface

The technology interface and platform play the critical collective intelligence role of instantly and continuously aggregating multiple participants' predictions into a single metric and making it publically available for other participants to view and respond to.

Market Information

Basic background information was provided to all participants through a supporting information tab within each prediction question in the technology platform. Examples are historic sales trends and planned distribution and promotional activities for existing products and concept boards for new concepts. Supporting information was provided by the research team of each SBU. There was much variation allowed in the information provided and its format to reflect the information commonly used within each unique SBU. Participants were selected to have at least some access to other company and market information, and they were encouraged to use additional internal and outside information. The combined collective prediction of all participants was posted publically, in real-time, through another tab under each prediction question in the technology platform (see Figure 3 for an example). In order to obtain an initial unbiased prediction from each participant, they were not able to see the combined prediction until they first entered their own initial prediction for each question.

Incentive Program

For a prediction market to be successful there needs to be many people participating, frequent activity, revelation of good information, and the desire to perform well (Hopman 2007). The incentives built into a market provide most of the motivation for these things to happen. The same incentive program was used in each operating division.

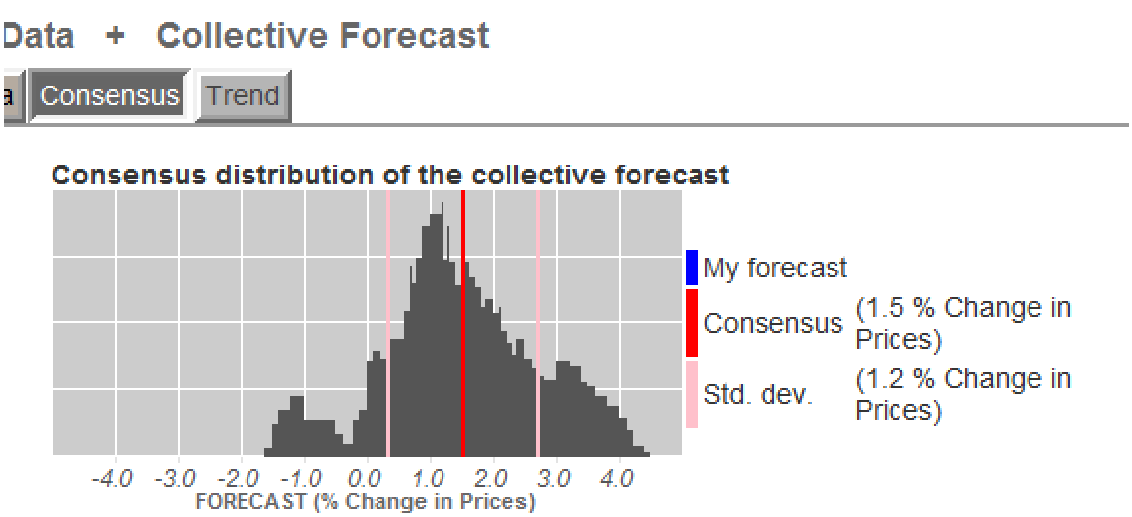

Figure 3. Example of Combined Collective Prediction

In each division, the top two performers earned $250 and $150 respectively. Five additional $50 prizes were awarded in each division through a lottery drawing where each participant owned a number of tickets in proportion to the total number of points they earned in the market. Thus, the more points earned, the more likely a participant is to own one of the five winning tickets. Points are earned by predicting correct forecast ranges, by indicating narrow confidence ranges, and by predicting early. Points are determined after actual outcome results become available and can be compared to predictions. Second, the incentive structure strongly rewards and motivates top performers. The scoring rules are designed to reward accuracy, precision, and timeliness: to win, it is not enough to be right, participants must also be right before the others. Forecasts are made by selecting a low-high range of possible values for the target variable. The difference between the high and low bounds is the spread of a given participant's forecast. Points are won only if the high-low range captures the outcome (accuracy). The number of points won is the same wherever the outcome falls in the selected range. It makes no difference whether the actual is closer to an edge or closer to the center of the range. Accurate forecasts with tighter spreads earn more points than accurate forecasts with larger spreads (precision). Typically, there is a maximum spread that cannot be exceeded. As shown on Figure 4, a correct forecast that uses the maximum spread could win 100 points per day, while tighter forecasts could win up to 500 points per day. The earlier a participant starts forecasting, the more points they may win (timeliness). Forecasts can be updated at any time and as many times as a participant wishes, and each update is scored independently for accuracy and precision, as explained above. The number of points a forecast earns for accuracy and precision are multiplied by the number of days that it remained unchanged before the next update. If a forecast is changed several times on the same day, only the last update is recorded, the others are discarded. When the target outcome is finally measured, each participant's final score will be the sum total of all the points earned for each forecast (total score). Each market rewarded seven winners, for a total of 21 winners total across all three SBUs. The Table 12 describes the various dollar amounts for the seven prizes awarded in each SBU's market. The total of $650 multiplied by 3 SBUs, yields total prizes of $1,950. For the lottery prizes, 5 drawings were made sequentially so that each drawing exempts all the tickets of the winner of the previous drawing. This means that the same participant cannot win two drawings in the same market. As soon as a participant wins one drawing, all his tickets are removed from the pool used for the remaining drawings. This winner-determination scheme has two desirable properties. First, every participant, at every level of performance, has a chance of winning a prize with those who perform better more likely to win a prize. Second, the incentives structure strongly rewards and motivates top performers.

Table 12. EPM Prize Structure

Rank	Value	Quantity	Total
1	$250	1	$250
2	$150	1	$150
Lottery	$50	5	$250
		7	$650

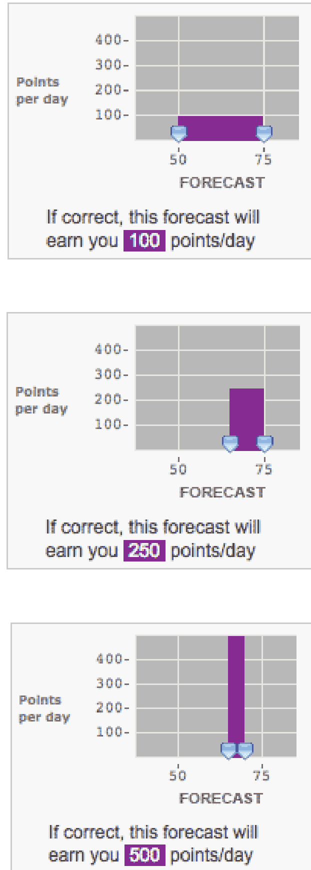

Figure 4. EPM Prize Scoring Illustration

Predicted Outcomes

Prediction Questions

For prediction markets to be successful, the outcomes to be predicted must be defined specifically and clearly and be easily understood by participants (Wolfers and Zitzewitz 2004; Soukhoroukova and Spann 2005). Predicted outcomes for this study have been selected to represent a wide range of typical marketing forecasts and decisions and a variety of research and forecasting methodologies used in practice. Three common categories of predicted outcomes are used in the analysis: new product sales, supply chain shipments, and overall division dollar sales forecasts. These categories were chosen to support three important decision areas in the marketing and forecasting literature: new product development, supply chain, and marketing return on investment (Srivastava, Shervani, and Fahey 1999). These three forecast types will be compared across each of the three operating divisions of the subject company. The resulting nine sets of data will provide greater evidence of construct validity (Armstrong 2001c). All of the questions pertain to outcomes that are months away from being realized and many of the questions have both short and long term forecasting horizons. The markets included several additional questions, unique to the operating divisions, related to new concept testing, category spending behavior, and macro industry and economic variables. Table 13 displays the three question types by SBU plus the additional questions. The additional questions pertaining to fuel, food, and pricing are common influential inputs to volumetric modeling within the subject company. The ability to predict them, months in advance, would provide advantage to decision makers in higher level forecasts and commitments. These questions also provide the opportunity to test prediction markets against traditional marketing survey techniques considered expensive and time consuming. All questions in the field test are real questions the subject company currently studies, forecasts, and uses in their annual operating plan; therefore, they have a high degree of relevance to management. For questions to be included they had to be an outcome that would be realized at least three months away, have a fair degree of uncertainty, could be predicted, pertained to a material business issue, had a corresponding internal forecast (or an externally published reference, e.g. Consumer Price Index), and have an objective established measurement in place. There had to be a question for each of the areas (considered core questions). And 2-3 additional questions were allowed per SBU. The questions are presented in Table 13 with the language from the system slightly disguised for confidentiality. In this table, Q2 FY12 and H1 FY12 refer to the second quarter and first half fiscal year 2012 respectively. These are explained further in the analysis section. Within the core question structure, questions were allowed to be worded and scaled uniquely per SBU to maintain realistic and useable outcomes and to compare exactly to existing internal forecasts. This also increases predictive validity (Armstrong 2001c).

Question Specification

Outcome specification is achieved through wording and scaling of the questions for each predicted outcome presented in the EPM system. Each question carefully specifies what is to be forecasted (e.g. dollars, units), when (e.g. quarter, annual), and where (e.g. geography, channel). The scales indicate a wide range of values within which actual outcomes may fall. Through the technology interface, participants indicate a confidence range around the outcome value they individually predict will actually occur. This can be seen on Figure 2. For each question, participants are asked to indicate on the scale on their computer screen, where they think the actual outcome value will fall in the future period. They can also adjust the range of their prediction to reflect their confidence level. With their curser, they are able to slide their confidence interval along the preset prediction scale and expand or contract their confidence interval by sliding the end points of this range. If the actual outcome value falls within their range they win points for that question, if the actual outcome value does not fall with their range they win zero points.

They also win more points by indicating higher confidence in their predictions; they do this by setting a narrower their range (see Figure 4 for illustration). In order to control information or bias that the scales may impart to participants, a consistent set of decision rules regarding the range, granularity, and central value were used to design the prediction scales. The ranges of the scales were based on the historic range of the outcome being predicted combined with the existing internal forecast. The midpoint of the scale is the middle of this combined range. The resolution of the scale is based on the size of the past five years' of changes in the outcome variable and the precision level of the existing internal forecast. Current, corresponding internal forecasts are not indicted on the scale or shared with the participants in order to avoid any anchoring bias that may occur due to confidence attributed to the perceived skill, experience, and knowledge of the internal forecasting teams.

Analysis and Results

Study I addresses the first research question: can prediction markets improve forecasting accuracy in marketing applications? The prediction market ran between August 10th and September 29th, 2011 to make predictions on sales and marketing outcomes for the subject company's fiscal second quarter which was November 2011 to January 2012. Actual results for the fiscal second quarter became available at the end of February 2012.

Table 13. Matrix of Prediction Market Questions

	SBU 1	SBU 2	SBU 3
New Products	For the pilot Channel A product racks, once the new Product A items have been placed, what will be the change in volume for the entire product category for Q2 compared to the same period a year ago?	What will be the U.S. unit sales for new Product B for Q2 FY12?	What will be the U.S. sales volume for newly launched Product C for Q2 FY12?
Supply Chain / Shipments	What will be the change in U.S. shipments to Customer B for Q2 FY12 compared to the same period a year ago?	What will be the change in shipments of Product Category C, to the U.S. grocery channel, for Q2 FY12 compared to the same period a year ago?	What will be the change in second year shipment volume for Product D, in the grocery channel, for Q2 FY12 compared to the same period a year ago?
Overall Sales	What will be the change in overall SBU1 Net Sales for Q2 FY12 compared to the same period a year ago?	What will be the change in net sales for total SBU 2, Category D for Q2 FY12 compared to the same period a year ago?	What will be the change in overall U.S. net sales for SBU 3, Brand A for Q2 FY12 compared to the same period a year ago?

Additional Questions	How will prices for food Away From Home have changed for the 12 months ending in November 2011 compared to the 12 months ending in November 2010?	What will the national average price for a gallon of regular unleaded gas be in the first week of November 2011?	What % of U.S. households will try new Product E during H1 FY12?
Additional Questions	If located in the perimeter of a grocery store, which of the following brand names would consumers perceive as providing the most attractive line of new Food Products?		See the concept below for Product F, a new product being developed. What will the Top 2 Box scores be for this new product concept? (i.e., the % of consumers likely rating ‘would buy' this concept.

Data Source and Set Up

The data for the first study comprises the prediction market forecasts, existing internal company forecasts, and actual market results. The prediction market forecasts were available from the technology platform as soon as the market closed. They are in the form of an aggregation of collective individual predictions and shared as distributions with measures of central tendency and variation. The existing internal company forecasts were produced during regular company planning processes before the market was established. These were shared during the market design process. Actual market results were reported through company sales reports after the study period closed. Units and levels of analysis are based on the product and geographic scope and the timeframe of each of the prediction market questions specified.

During August and September 2011, 154 internal employees made 1460 predictions across 22 questions. The questions are described in the previous prediction questions and specification sections. The 154 participants self-selected any number of the 22 questions across the three SBUs to make their predictions. Participants were also able to update their predictions any number of times. Table 14 shows the mean and mode number of predictions made by individual participants (including updates) are nine and seven respectively with a range of 1-21.

Table 14. Prediction Activity by Individual Participants

Individual Predictions	
Mean	9
Range	1-21
Mode	7

Tables 15 through 18 summarize prediction activity by participant function, participant SBU/division, participant employment tenure, and by SBU question. From these tables it can be seen that almost 70% of predictions are from participants from the R&D, Marketing, and Supply Chain functions; the most predictions came from SBU2 (which is the largest SBU and has the most participants); predictions come from participants with various tenures but less from those with more than 10 years; and the most predictions were made against questions from SBU2. This last fact can be explained by SBU being the core business of the subject company with many people in other functions having worked in this SBU and having knowledge about its business. These distributions are consistent with those shown previously for the distributions of participants.

As described in the question specification section, EPM participants submitted their predictions as ranges in the system and they could return and submit new ranges any time while the market was open. The data point captured from the system and used in the analyses for studies one and two is the range for each participant's final estimate at the market close. The midpoint of each range is taken as a point estimate for the analysis that follows.

Table 15. Prediction Activity by Function

Function	Frequency	Valid Percent
Fin	113	7.7
HR	1	0.1
Insights	91	6.2
Marketing	285	19.5
Other	40	2.7
R&D	464	31.8
Sales	138	9.5
Supply Chain	270	18.5
Total	1460	100.0

Table 16. Prediction Activity by SBU/Division

Division	Frequency	Valid Percent
SBU1	272	18.6
SBU2	680	46.6
SBU3	244	16.7
Corp	112	7.7
Other	94	6.4
Total	1460	100.0

Table 17. Prediction Activity by Tenure

Tenure	Frequency	Valid Percent
0_2	368	25.2
3_5	420	28.8
6_10	366	25.1
11_20	156	10.7
21_on	92	6.3
Total	1460	100.0

Table 18. Prediction Activity by SBU Questions

SBU Questions	Frequency	Valid Percent
SBU1	333	22.8
SBU2	629	43.1
SBU3	440	30.1
Total	1460	100.0

Comparative Accuracy Analysis

For each of the 22 questions tracked from the EPM market and system, Table 19 presents the data used in the analysis. Predictions are identified by SBU, question name (e.g. New Product Dollar Sales), and question type (NP=New Products, SC=Supply Chain, OS=Overall Sales, and O=Other). The abbreviated question names on this table correspond directly with the descriptions provided previously in Table 13 in the prediction questions section. For each prediction, the units of measure and number of final estimates (n) are also indicated. In order to produce results that were directly comparable to existing internal forecasts, each SBU was permitted to establish their own units of measure for their prediction questions. In Table 19, 000s corresponds to thousands of units, MM to millions of units, % Chng to percentage change, and $ to dollars.

In order to set up the accuracy analysis, deviation from actual outcomes (in the original measurement units) is calculated for the EPM aggregate prediction (EPM Pred), the internal forecast (Internal FCST), and for a combined forecast (Comb FCST). The internal forecasts and actual values were provided by the internal forecast teams and research directors of each SBU for their respective prediction questions. Descriptions of these teams are provided in Table 30 in the methodology description for Study II. The internal forecasts were provided during the EPM market design phase as they were already established and published by the internal forecast teams. The actual values were not available until the forecasted time periods were actually completed and the company processed, closed their books, and provided official final numbers five months after the EPM closed. For five prediction questions both a second fiscal quarter (Q2) and a fiscal first half (H1) were predicted as separate prediction questions in the EPM system. These forecast periods are indicated in the question name (Q2 and H1) for these questions. For each question, the EPM Aggregate Prediction is the simple average of the midpoints of all participants' final ranges submitted for that prediction question. This value is essentially the aggregation of multiple participants predictions for a particular question; the collective intelligence of that group. The combined forecast is the average of the EPM aggregate prediction and the internal company forecast. Two approaches to assessing whether prediction markets can improve forecasting outcomes are considered in this study. One is to compare the EPM aggregate prediction directly against the internal forecast relative to actual outcome (head to head comparison). Another approach is to combine the EPM aggregate prediction with the internal forecast to assess how accurate the combined forecast is relative to the actual outcome. The previous forecasting section in chapter two provides background and evidence for the improvement to forecasting outcomes from combining methods (Clemen 1989). The combined forecasts are also included because they more closely reflect what is done in practice; seldom are important final company forecasts based on one set of data or model. For example, Kahn (2002) finds that companies typically use 2-4 forecasting techniques in new product processes.

Combining forecasts could also be viewed as updating the company's existing internal forecast with a sample of data from the prediction market.

The values displayed in Table 19 are deviations of the EPM aggregate prediction, the internal forecast, and the combined forecast from actual outcome values. Note that each question had a different group of predictors as indicated by the various n values; participation ranged from 45 to 97 employees depending on the question. Also note that out of 22 prediction questions on Table 19, only 17 have deviation values to be used in comparisons of EPM aggregate predictions and combined forecasts against internal forecasts and actual results. The question about Brand Preference is a categorical question that has no mean value, internal forecast, or actual outcome. Also, the questions about Average Price of Gas, New Product IntentA, and New Product IntentB have no comparable internal forecasts. This results in their exclusion from the analysis steps that follow.

Table 20 introduces the comparative accuracy analysis. In forecasting, accuracy refers to the accuracy of the future forecast compared to the actual outcome. The forecaster's goal is to minimize the deviations or errors that are the difference between the actual value and what was forecasted. For this reason, accuracy is often measured by its error value. The forecasting literature indicates several measures of forecast accuracy. Several more common measures include correlation with actual outcomes, absolute error, mean absolute error, absolute percentage error, mean absolute percentage error, and standard deviation of error (Dalrymple 1987; Wolfers and Zitzewitz 2004; Armstrong 2006; Armstrong and Collopy 1992; Mahmoud 1994). The most common methods are relative measures of accuracy provided by absolute percentage error (APE) and mean absolute percentage error (MAPE) (Armstrong and Collopy 1992).

The focal measure for this analysis is absolute percentage error (APE); it is scale free enabling a comparison across predictions of different scales and it is sign free allowing for mean calculations (Armstrong 2001c; Armstrong and Collopy 1992). For each question, an APE is calculated that compares the error between the actual outcome and the predicted or forecasted outcomes. The formula to be used is as follows:

$$APE_i = |Actual_i – Forecast_{ij}| / Actual_i$$

Where i represents prediction questions 1-17 and j represents forecast method as EPM Pred, Internal FCST, or Comb FCST. Table 21 and Figure 5 present data that describes the nature of the of the 1,402 EPM predictions made over the 17 questions. The mean APE value is 0.85 with a standard deviation of 0.94 and a range of 0 to 10.6. The single APE value of 10.6 is very large and a potential outlier. Trimming the most extreme 5% of predictions, however, had a very small non-significant effect on the mean value of the EPM aggregate predictions. This is effect has also been found in the forecasting literature (Jose and Winkler 2008). Upon inspection, this is found to be due to the EPM aggregate predictions averaging small and large negative and positive errors that cancel each other out in a consistent manner. Note that the distribution in Figure 5 is based on absolute values of APE.

Table 19. Comparative Deviation from Actual

SBU1	Units	Type	n	Deviation from Actual: EPM Pred	Internal FCST	Comb FCST
New Product Dollar Sales	% Chng	NP	73	1.35	-2.00	-0.33
Supply Chain Unit Ship	% Chng	SC	69	4.54	8.00	6.27
Overall Dollar Sales	% Chng	OS	65	-8.83	-8.00	-8.42
Overall Net Profit Dollars	% Chng	OS	64	-33.12	-35.00	-34.06
Average Food Price	% Chng	O	62	-1.15	na	na
Brand Preference	na	O		na	na	na
SBU 2						
New Product Q2 Unit Sales	MM	NP	97	0.02	0.30	0.16
New Product H1 Unit Sales	MM	NP	89	0.51	0.44	0.48
Supply Chain Q2 Unit Ship	% Chng	SC	87	4.57	-7.50	-1.47
Supply Chain H1 Unit Ship	% Chng	SC	87	4.93	-5.00	-0.03
Overall Q2 Dollar Sales	% Chng	OS	88	1.64	2.00	1.82
Overall H1 Dollar Sales	% Chng	OS	89	2.55	0.20	1.38
Average Price of Gasoline	$	O	92	0.19	na	na
SBU3						
New Product Q2 Unit Sales	000s	NP	53	53.06	22.91	37.99
New Product H1 Unit Sales	000s	NP	49	56.62	64.90	60.76
Supply Chain Q2 Unit Ship	% Chng	SC	45	60.50	90.55	75.53
Supply Chain H1 Unit Ship	% Chng	SC	48	28.19	34.40	31.30
Overall Q2 Dollar Sales	% Chng	OS	48	2.09	2.02	2.05
Overall H1 Dollar Sales	% Chng	OS	48	6.74	5.72	6.23
New Product Trial	%	O	48	0.69	1.67	1.18
New Product Purch IntentA	%	O	51	17.90	na	na
New Product Purch IntentB	%	O	50	23.34	na	na

Table 20. Comparative Absolute Percentage Errors (APE)

SBU1	Units	Type	n	Error (APE) EPM Pred	Internal FCST	Comb FCST
New Product Dollar Sales	% Chng	NP	73	67.3%	100.0%	16.4%
Supply Chain Unit Ship	% Chng	SC	69	227.1%	400.0%	313.6%
Overall Dollar Sales	% Chng	OS	65	88.3%	80.0%	84.2%
Overall Net Profit Dollars	% Chng	OS	64	89.5%	94.6%	92.1%
Average Food Price	% Chng	O	62	39.5%	na	na
Brand Preference	na	O		na	na	na
SBU 2						
New Product Q2 Unit Sales	MM	NP	97	1.3%	19.0%	10.1%
New Product H1 Unit Sales	MM	NP	89	21.4%	18.3%	19.9%
Supply Chain Q2 Unit Ship	% Chng	SC	87	53.8%	88.2%	17.2%
Supply Chain H1 Unit Ship	% Chng	SC	87	54.8%	55.6%	0.4%
Overall Q2 Dollar Sales	% Chng	OS	88	74.5%	90.9%	82.7%
Overall H1 Dollar Sales	% Chng	OS	89	77.3%	6.1%	41.7%
Average Price of Gasoline	$	O	92	5.8%	na	na
SBU3						
New Product Q2 Unit Sales	000s	NP	53	48.9%	21.1%	35.0%
New Product H1 Unit Sales	000s	NP	49	21.1%	24.1%	22.6%
Supply Chain Q2 Unit Ship	% Chng	SC	45	112.7%	168.6%	140.6%
Supply Chain H1 Unit Ship	% Chng	SC	48	127.0%	155.0%	141.0%
Overall Q2 Dollar Sales	% Chng	OS	48	59.2%	57.2%	58.2%
Overall H1 Dollar Sales	% Chng	OS	48	85.3%	72.4%	78.9%
New Product Trial	%	O	48	50.9%	123.4%	87.2%
New Product Purch IntentA	%	O	51	47.9%	na	na
New Product Purch IntentB	%	O	50	84.0%	na	na
Overall Error (MAPE): Corresponding Preds				74.1%	92.6%	73.0%

Table 21. Descriptive Statistics for EPM Individual Prediction Errors

	Descriptive Statistics					
	N	Range	Min	Max	Mean	Std. Dev.
APE Measure	1402	10.6	0.0	10.6	0.85	0.94

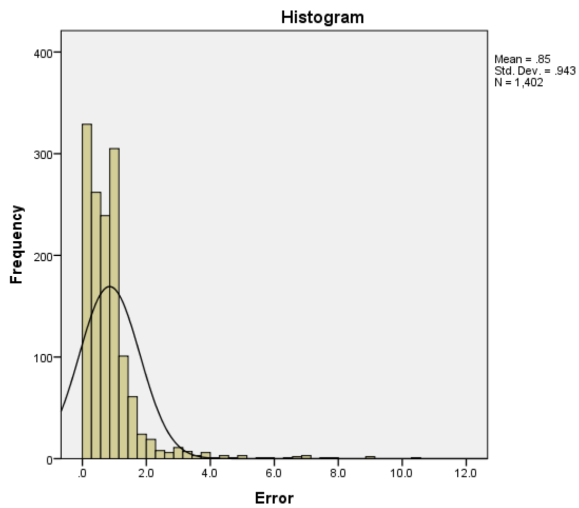

Figure 5. Distribution of EPM Individual Absolute Prediction Errors

Based on the APE formula described, Table 20 summarizes the APE values for the EPM aggregate predictions, the internal forecasts, and combined forecasts. Reviewing this table indicates that APE values range widely from 1.3% to 227.1% for the EPM predictions, 6.1% to 400.0% for the internal forecasts, and 0.4% to 313.6% for the combined forecasts. The most accepted measure to compare groups of predictions is Mean Absolute Percentage Error (MAPE) (Armstrong and Collopy 1992; Armstrong 2001c). In this analysis, the MAPE is simply a mean of the APE values for a particular type of prediction or forecasts. The bottom of Table 20 indicates the MAPE values for the EPM predictions, internal forecasts, and combined forecasts of 74.1%, 92.6%, and 73.0% respectively. In line with their wide forecast ranges, these means have significant standard variations of 0.51, 0.92, and 0.76 respectively. Note that these values do not include the data from the questions regarding Brand Preference, Average Price of Gas, New Product IntentA, and New Product IntentB as they have no comparable internal forecast. A comparison of these MAPE scores using ANOVA indicates that these mean values are not significantly different from each other (F=0.366 with 51 degrees of freedom and p=0.695). Due to the forecasts being so different from each other in their subject, nature, and variance, they are not realistically or reasonably comparable in terms of a significance test (Armstrong 2001b). This finding may also exhibit what Cook and Campbell (1979) refer to as an issue of statistical conclusion validity where irrelevant variation inflates the error term and obscures true differences. For example, in this case the entire comparison between forecast methods can be significantly biased (dominated) by one or two prediction questions with widely different outcomes. According to Armstrong's (2001a) work on comparing forecasts, if the forecasts are reasonably comparable, such as a time series of the same outcome, then a significance test of the MAPE comparison would be appropriate.

Two alternative comparison measures that are deemed to be highly reliable are Relative Reduction in Error (RRE) and Percent Better (PB) (Armstrong 2001c; Armstrong and Collopy 1992). A measure of Relative Reduction in Error compares the reduction in error offered by an alternative forecast method compared to the traditional forecast method: in this case EPM predictions and combined forecasts compared to the internal forecasts. The formulae for this analysis would be the following:

$$\text{EPM Pred RRE}_i = \text{Internal FCST APE}_i - \text{EPM Pred APE}_i$$

$$\text{Comb FCST RRE}_i = \text{Internal FCST APE}_i - \text{Comb FCST}_i$$

Where i=1-17 for the 17 questions where the Error (APE) for EPM predictions and combined forecasts can be compared to an internal forecast. Table 22 summarizes relative error reduction across prediction questions for the EPM predictions and combined forecasts compared to the internal forecasts. Error reduction values range from (71.2) to 172.9 for the EPM predictions and from (35.61) to 86.45 for the combined forecasts. This means for example, the EPM predictions range from performing 71.2 points worse to 172.9 points better than the company's set of internal forecasts in terms of APE. This assessment is enhanced by combining it with the Percent Better assessment which is the ratio of predictions that have a positive error reduction (RRE) to all predictions. The Percent Better (PB) formulae for this analysis would be the following:

EPM Pred PB = (# of positive EPM Pred RREs) / (Total # of Predictions) x 100

Comb FCST PB = (# of positive Comb FCST RREs) / (Total # of Predictions) x 100

Based on the values in Table 22, the Percent Better ratio for the EPM predictions and the combined forecasts would be 64.7% (11 out of 17 questions). Therefore, nearly two thirds of the time, the EPM predictions and the combined forecasts provide a forecast that is an improvement over the existing internal forecast. The results partially support hypothesis one,

> H1: The aggregate forecasts of prediction markets are more accurate than forecasts produced by the traditional methods used within major firms.

In addition, the EPM aggregate predictions reduce the forecast error range by over 40% compared to the internal forecasts. Recall from Table 20, APE values range from 1.3% to 227.1% for the EPM predictions, 6.1% to 400.0% for the internal forecasts, and 0.4% to 313.6% for the combined forecasts. The non-significant reduction in MAPE found earlier between EPM predictions and the existing internal forecast are consistent with results in the literature that find two methods exhibit statistically equal performance on this measure (Grucca, Berg, and Cipriano 2003). The results of the present study serve to replicate and support those of previous studies. The 65% percent better ratio found in this analysis is slightly lower than the results from comparable analyses (75%) completed for Hewlett Packard by Ho and Chen (2007) and for Intel completed by Hopman (2007).

Comparing EPM predictions and the combined forecasts on Tables 23 and 24, the only time combined forecasts offer an advantage over the EPM predictions is for SBU2; in this case about three quarters of the time the combined forecast offers improved accuracy over the EPM prediction. This may be due to the relative maturity of SBU2 within the company and the greater amount of and quality of data available and their superior forecast accuracy. Across the dimensions of new products, supply chain, sales, or long term vs. short term time horizon, the combined forecast offers improved accuracy in only half or less of the cases. It is interesting to note that in every one of the six cases where the EPM prediction was worse than the internal forecast, the combined forecast reduced the relative negative performance of the EPM prediction compared to the internal forecast.

Table 22. Relative Reduction in Errors

SBU1	Units	Type	n	Relative Reduction in Error (RRE) EPM Pred	Comb FCST
New Product Dollar Sales	% Chng	NP	73	32.7	83.6
Supply Chain Unit Ship	% Chng	SC	69	172.9	86.4
Overall Dollar Sales	% Chng	OS	65	(8.3)	(4.2)
Overall Net Profit Dollars	% Chng	OS	64	5.1	2.5
Average Food Price	% Chng	O	62	na	na
Brand Preference	na	O		na	na
SBU 2					
New Product Q2 Unit Sales	MM	NP	97	17.8	8.9
New Product H1 Unit Sales	MM	NP	89	(3.1)	(1.6)
Supply Chain Q2 Unit Ship	% Chng	SC	87	34.5	71.0
Supply Chain H1 Unit Ship	% Chng	SC	87	0.8	55.2
Overall Q2 Dollar Sales	% Chng	OS	88	16.4	8.2
Overall H1 Dollar Sales	% Chng	OS	89	(71.2)	(35.6)
Average Price of Gasoline	$	O	92	na	na
SBU3					
New Product Q2 Unit Sales	000s	NP	53	(27.8)	(13.9)
New Product H1 Unit Sales	000s	NP	49	3.1	1.5
Supply Chain Q2 Unit Ship	% Chng	SC	45	56.0	28.0
Supply Chain H1 Unit Ship	% Chng	SC	48	28.0	14.0
Overall Q2 Dollar Sales	% Chng	OS	48	(1.9)	(1.0)
Overall H1 Dollar Sales	% Chng	OS	48	(12.9)	(6.5)
New Product Trial	%	O	48	72.5	36.2
New Product Purch IntentA	%	O	51	na	na
New Product Purch IntentB	%	O	50	na	na
Overall Error (MAPE): Corresponding Preds				18.5	19.6

Mathematically this is because the combined forecast combined the performance of the EPM prediction and the internal forecast to which it is being compared. Other than this benefit, the combined forecasts offered no advantage over any of the dimensions of SBU, question type, or forecast horizon.

The performance of the EPM can also be assessed across dimensions such as business unit and question type. As can be seen on Table 23, the EPM appears to offer the greatest error reduction to SBU1 which is a B2B foodservice producer. SBU2 is a consumer packaged goods prepared foods producer and SBU3 is a consumer packaged goods beverage bottler. Similarly, on Table 24, the EPM appears to offer greater error reduction on the Supply Chain and New Product questions. All of these instances where the EPM predictions perform better are ones for which there is limited information and knowledge to support the prediction or forecast. The advantage is rooted in the markets' ability to generate new and different information for a prediction task. With the first research question answered in the affirmative, the next chapter will present Study II which investigates the second research question: how do prediction markets improve marketing forecast accuracy? The market's ability to generate new and different information for a prediction task in addition to other factors from the theoretical framework will be tested with empirical data from a post survey of participants that followed this same EPM implementation.

Table 23. Comparative Accuracy Analysis by SBU

	Error (MAPE)			Error (MAPE) Reduction	
	EPM Pred	Internal FCST	Comb FCST	EPM Pred	Comb FCST
SBU1	118.1%	168.6%	126.5%	50.6	42.1
SBU2	47.2%	46.4%	28.7%	(0.8)	17.7
SBU3	72.2%	88.8%	80.5%	16.7	8.3

Table 24. Comparative Accuracy Analysis by Question Type

	Error (MAPE)			Error (MAPE) Reduction	
	EPM Pred	Internal FCST	Comb FCST	EPM Pred	Comb FCST
New Products	32.0%	36.5%	20.8%	4.5	15.7
Supply Chain	115.1%	173.5%	122.6%	8.4	0.9
Overall Sales	76.9%	61.3%	69.1%	(15.6)	(7.8)
Other	44.3%				

In addition to the forecast point estimates provided by prediction markets and assessed here, prediction markets also provide a measure of uncertainty for each forecast. This is in the form of a probability distribution for each question based on the distribution of all participants' estimates (Wolfers and Zitzewitz 2004; Berg, Neumann, and Rietz 2009). Figure 3 displays an example distribution for an actual question for this project.

When assessing the performance and value of prediction markets, it is important to consider the other dimensions of forecasting research. For example, in cases where prediction markets provide estimates with accuracy equal to traditional methods, prediction markets may be less expensive, faster, and easier to implement compared to popular established methods (Gruca, Berg, and Cipriano 2003; Ho and Chen 2007; Spann and Skiera 2003). These benefits alone may justify the use of prediction markets to support marketing forecasting.

CHAPTER 5

STUDY II METHODOLOGY AND RESULTS

The conceptual framework presented in Figure 1 is proposed as a structural model of relationships amongst several latent constructs that can be measured through a corresponding measurement model based almost entirely on scale items as sets of indicator variables. Study II analysis will begin with an assessment of the psychometric properties of the measurement model. Descriptive statistics, factor analysis, confirmatory factor analysis, and reliability analysis will be performed to assess validity and reliability of the measurements presented. Standards techniques and statistical tests for these methods will be presented. The structural model will be analyzed and parameters estimated through structural equation modeling. The latent constructs (new information acquisition, differences in interpretation, use of shared information, knowledge heterogeneity, forecast independence, and incremental incentive) will be treated as exogenous independent variables and the prediction market's forecast accuracy will be treated as the measured dependent variable. Standard techniques, test statistics, and indices for SEM will be used to assess the measurement model and estimate path coefficients to explain the existence and strength of relationships proposed by the conceptual framework.

Participants and Procedures

The sample frame of respondents for the post market survey was selected from the pool of 154 participants that completed at least one core prediction question in Study I, the EPM implementation. A questionnaire was distributed to all prediction market participants, through an internal email from a senior executive (VP Research), thanking them for participating in the initial study. This email included an invitation to provide feedback on their experience with the EPM by participating in a post survey. A link to the Qualtrics website and the questionnaire was embedded in the email (see Appendix B for a copy of this communication). Similar to the EPM recruitment program in Study I, the implementation procedures and schedule of contact activity for the EPM post survey were designed according to the tailored design method (Dillman Smyth, and Christian 2009) to maximize survey response quantity and quality. The number and timing of contacts were carefully programed and executed to achieve these goals; as have the format, content, and style of communications; the sources of communications; and the number and nature of the inducements.

Table 25 and supporting exhibits in Appendix B demonstrate how the recruitment program for Study II was accomplished. For example, based on the advice of Dillman and colleagues, contacts were personalized, there were multiple strategically timed contacts, contact messages were varied, contacts were brief, and subject lines were carefully written. In addition, to establish trust, high level sponsorship was used, the importance of the task was emphasized, and confidentiality was assured. To increase benefits of participation, the survey was explained, help was asked for, thank yous were made, tangible rewards were offered, the task was made interesting, and exclusivity of participation was established. Finally, to decrease personal costs of participation, ease of access and shortness of survey was demonstrated, no request for personal information was established, and the task was described as routine.

Respondents were offered the chance to win one of three iPads for participating in the survey and were told that the survey would be open for three weeks. They were also encouraged to participate as part of a new initiative that might help improve research tools and their business. Over a period of three weeks, respondents were sent three waves of reminder communications, timed one week apart, from different internal employees related to the project. To increase awareness and interest and to encourage participation, drawings and announcements of the three iPad winners were staggered to coincide with the waves of reminders. This produced 84 completed surveys. In order to increase sample size, a second round of incentives was offered to potential respondents who had not yet participated: a $10 Starbucks gift certificate for completing the survey. Based on the second round of recruiting, 19 additional surveys were completed for a total of 103 completed questionnaires submitted to the Qualtrics system producing an overall response rate of 67%. Due to programing in the questionnaire design, all completed submissions were useable.

An analysis of possible nonresponse bias compared wave one to wave two respondents on organizational demographics and question responses. Respondents in wave two were similarly distributed as wave one, across the captured organizational demographics of business unit, function, and tenure.

Table 25. Post Survey Recruitment Procedures

Purpose/Source	Timing	Format	Audience	Content
Wave 1 Announcement /VP Research	10/13/11	Formal email	EPM participants	Thank you for EPM participation Introduce and explain post survey Explain importance and benefits Announce rewards and drawings Explain assistance to PhD student Share link to post survey
Wave 2 Reminder /VP Research	10/20/11	Informal email	Remaining EPM participants	Friendly reminder Announce drawing of first prize pending Share time remaining Reminder of assistance to PhD student
Wave 3 Final Reminder /VP Research	10/28/11	Update email	Remaining EPM participants	Announce first prize winner Final reminder and survey closing date Explain importance and benefits Announce drawing of second prize Thank you for participating
Wave 4 Personal request /SBU Research Directors	11/2/11	Personal email	Remaining EPM sample within SBU	Personal request to participate to achieve sample size goals Offer of special incentive Announce drawing of third prize Attach prior invitation with link Indicate extended closing date

There were, however, significant differences in four scale item means scores between wave one and wave two respondents. All of these questions were monitored for the remainder of the analysis and three were eventually removed during the scale purification exercise. The one remaining question presents no meaningful concern for the analysis and tests as it is one of six scale items for a single construct and does not display any distinctive results. Therefore nonresponse bias is not considered to be an issue. Tables 26, 27, and 28 display organizational demographic data for the final respondent pool.

Table 26. Post Survey Respondents by Function

Function	Freq	%
R&D	33	32.0
Marketing	24	23.3
Supply Chain	18	17.5
Sales	9	8.7
Insights	8	7.8
Fin	7	6.8
Other	3	2.9
Total	103	100.0

Table 27. Post Survey Respondents by Business Unit

Business Unit	Freq	%
SBU1	28	27.2
SBU2	52	50.5
SBU3	15	14.6
Corp	5	4.9
Other	2	1.9
Total	103	100.0

Table 28. Post Survey Respondents by Tenure

Tenure	Freq	%
0_2	29	28.2
3_5	30	29.1
6_10	25	24.3
11_20	13	12.6
21_on	5	4.9
Total	103	100.0

In line with the demographic data of the sample frame, survey respondents are primarily from R&D, Marketing, and Supply Chain; numbers for SBUs are in line with SBU relative sizes; and the majority of respondents have tenure of 10 years or less with the company.

The electronic online questionnaire was constructed in Qualtrics; it contains scale items for six model constructs’ and several other demographic and system assessment questions. The survey was introduced and described as an external project conducted by academics of Temple University to study the functioning of prediction markets and assess how they might aide their company in the future. The Qualtrics survey was programmed to capture each respondent’s EPM system username in order to append individual post survey results to individual EPM prediction data for later modeling and analysis.

Research Design

The overall research approach of this dissertation is based on a comparison of accuracy and functionality between i) a prediction market and is participants and ii) internal forecasts and their respective teams. Studies one and two compare the process and outcomes of the prediction market relative to the internal forecast methods.

Therefore the prediction market and its forecast is the treatment condition and the internal forecast method is the control. Study I compares prediction market and internal forecasts directly using standard error measures. In parallel with the accuracy comparison of Study I, Study II compares the prediction market against the internal forecast methods in terms of participant characteristics and activities, information used, system interface, and processes followed.

It is proposed that the EPM design produces the EPM predictions and their level of accuracy. It is observed that the traditional forecasting methods produce the internal forecasts and their level of accuracy. Study I compares the outcomes: the EPM predictions against the internal forecasts in terms of accuracy levels in order to determine whether the EPM is a superior alternative. In parallel, Study II compares the processes: the EPM design against the traditional forecasting methods in order to determine what aspects of EPM design produce the superior outcomes. Therefore Study II has two dimensions: i) how is the EPM design different from the traditional forecasting methods and ii) how are these EPM differences related to EPM accuracy levels? The hypotheses state that for higher levels of each of the design factor, the accuracy of the prediction market forecasts increases. In Study II, the levels of each EPM design factor (as the treatment condition) will be measured relative to the traditional forecasting methods (as the control). A comparison of the EPM design factors against traditional methods is largely a comparison of the EPM participant pool and what they did (the collective) against the internal forecast team and what they did. Recall, participants could make predictions on any EPM questions they chose. In addition, each internal forecast was completed by a different internal team and method. These two facts result in each EPM prediction question having a different participant pool (n ranging from 45 to 97) and each corresponding internal forecast having a different internal forecast team. This requires the level of analysis for Study II to be the individual prediction question. At this level, an EPM prediction question, its participant pool, its accuracy, and its corresponding internal forecast method can all be connected. One way to accomplish this is to have each EPM participant select one of the EPM prediction questions they estimated in the market, assess the levels of the EPM design factors relative to the corresponding internal forecast method, and correlate this difference to that EPM participant's accuracy for that same prediction question. The questionnaire will accomplish this through self-assessments made by the prediction market participants (as the treatment group) of the degree of difference or distance from the internal forecast team (as the control group). The first question of the questionnaire instructed respondents to select from a list, one EPM prediction that they made in the original EPM exercise that they could recall well. Each respondent's selected EPM prediction was then piped into all of the following scale questions and used as a point of reference. Table 29 displays the distribution of the nine prediction questions self-selected by the 103 respondents. Because participants could choose the prediction they were to evaluate from nine options and each of the nine prediction questions corresponded with a different internal forecast team, there was an issue of providing effective reference points as the control condition for the assessments. This is solved by providing a unique reference for each of the nine prediction questions that describe who the internal forecast team is, what information they have, and the process they follow to make their forecasts.

Table 29. Post Survey EPM Prediction Questions Selected

Prediction Question Selected	Frequency	Valid Percent
SBU1 New Products	5	4.9
SBU1 Supply Chain	10	9.7
SBU1 Overall Sales	13	12.6
SBU2 New Products	21	20.4
SBU2 Supply Chain	11	10.7
SBU2 Overall Sales	23	22.3
SBU3 New Products	13	12.6
SBU3 Supply Chain	4	3.9
SBU3 Overall Sales	3	2.9
Total	103	100.0

Each prediction market participant, as a post survey respondent, can then select the prediction they will evaluate and be shown a description of the corresponding internal forecast method for their comparisons. Table 30 shows the nine reference statements provided to respondents in the post survey.

The participants' self-assessments of the difference between themselves and the control reference group is made on seven point likert scales similar to those used by Li and Calantone (1998) in their self-assessments of knowledgeability. There is support for the use of group comparison scales in both the new products and forecasting literatures. Calantone and Di Benedetto (1988) use assessments relative to another group (competition) regarding market intelligence and company technical and marketing skills. Cooper and Kleinschmidt (1987) describe the importance of using a control group or reference group for comparison in order to identify characteristics which discriminate between commercial successes and failures.

Table 30. Post Survey Reference Statements for Internal Forecasts

Prediction Question	Internal Forecast Reference Statement
SBU1 New Products	This forecast is typically made by the Brand Marketing Team using input from the Customer Sales Team.
SBU1 Supply Chain	This forecast is typically made by the Brand Marketing Team using historical trend data on shipments and the Marketing calendar.
SBU1 Overall Sales	This forecast is typically made by the Finance Group using sales projections and Marketing spending data.
SBU2 New Products	This forecast is typically made by the Forecasting Group using consumer data and volumetric modeling from Marketing Research.
SBU2 Supply Chain	This forecast is typically made by the Forecasting Group using Sales plans, Marketing (spending), and Finance (AOP) information.
SBU2 Overall Sales	This forecast is typically made by the Forecasting Group using Sales plans, Marketing (spending), and Finance (AOP) information.
SBU3 New Products	This forecast is typically made by the Forecasting Group using overall Sales plans for the brand, assumptions about distribution, Marketing (spending), and Finance (AOP) information.
SBU3 Supply Chain	This forecast is typically made by the Forecasting Group using historical shipments data, Sales plans, Marketing (spending), and Finance (AOP) information.
SBU3 Overall Sales	This forecast is typically made by the Forecasting Group using historical shipments data, Sales plans, Marketing (spending), and Finance (AOP) information.

Batchelor and Dua (1995) uses self-assessed differences in opinion/thinking regarding economic theories to create an individual distance measure from a group average and find, for example, the greater the difference in opinion/thinking, the greater the reduction in forecast error.

The concept of scaling group differences and distance measures has foundations in the social psychology literature. Liberman, Trope, and Stephan (2007) describe psychological distance as perceived distance from oneself and other things such as different times, geographies, or people (including other peoples' perspective or ideas). In marketing, Maltz and Kohli (1996) measure difference between groups along several dimensions including a distance measure for interfunctional relationships. In the organizational literature, March (1991) contrasts the effects of organizational members being closer or farther from the current organizational knowledge base. Following this approach, differences in individual forecast accuracy will be compared directly to individual self-assessed, self-reported differences between prediction market participants (as the treatment group) and the internal forecast team (as the control group) through post survey scales for the EPM design factors in the conceptual framework. Following are three examples of the scaled group comparisons pertaining to post survey questions for knowledge heterogeneity, new information acquisition, and differences in interpretation:

Compared to the above description, to what degree did you …
    Have different knowledge than the people in the description?
    (1-very similar…7- very different)

In making your EPM prediction, to what degree did you…
    Try to search for different information than in the description?
    (1-not at all…7-a great extent)

In making your EPM prediction, to what degree did you…
Follow a different approach, process, or analysis than that in the description?
(1-not at all…7-a great extent)

All of the scales and questions are developed and described in detail in the sections that follow in this chapter. To complete the dataset for Study II, each respondent's EPM prediction for their selected prediction question (from Study I) is compared to the corresponding actual value and an individual error value (APE) appended to their post survey record. This error value (APE) serves as the dependent variable in the analysis and the self-assessed differences between the EPM design factors and the corresponding internal forecast serve as the independent variables.

Measures and Validation

Measures

There are six constructs from the conceptual framework for prediction markets forecasting that will be measured by reflective multi item scales: the market knowledge factors of i) new information acquisition, ii) differences in interpretation, and iii) use of shared information and the collective intelligence factors of iv) knowledge heterogeneity, v) forecast independence, and vi) incremental incentive. Measures for the constructs were developed in three stages.

In the first stage, based on the defined constructs, tentative measures were either borrowed or developed from academic research studies on related topics. Scale items for each construct are drawn from the literatures for market information processing, organizational management, collective intelligence, and several other native domains.

Specific wording and phrasing for the items is heavily influenced by these literatures. In a few cases exact scale items from the literature are used, in many cases scale items from the literature are adapted or combined into scales for this study, and in a few cases theory is relied on to develop new scale items. In the second stage, to assess face and content validity, a list of defined constructs and a randomized list of scale items were submitted to a panel of six senior marketing and management academics. They were requested to assign each scale item to the construct they believed was appropriate and note whether they thought any important dimensions that could also represent the construct were missing. The same task was given to two industry expert practitioners. From this exercise, several scale items were added, edited, combined, or removed. In a third stage, a pretest of the measures was completed in order to further assess scale comprehension, survey duration, logic and flow, and preliminary scale psychometric properties. A prediction simulation was given to 30 undergraduate students based on topics relevant to them and under conditions that replicated the prediction market information and estimation dynamic. They then completed a preliminary version of the post survey. The results of the preliminary post survey were used for preliminary assessment of reliability and validity of the measures, to determine the final set of scale items, and to adjust questionnaire wording and design. From these exercises and adjustments, final scale items and wording were determined and are summarized in Appendix C. The following paragraphs describe specific process and theoretical support for each scale construct and its scale items.

New information acquisition is defined as participants searching for and obtaining additional or different information to use in their individual predictions. It is measured by a ten item scale adapted from studies by Moorman 1995; Moorman 1990; Li and Calantone 1998; Baker and Sinkula 1999; Kohli, Jaworski, and Kumar1993; Slater and Narver 2000; and Chaston, Badger, and Sadler-Smith 2000. These scales assess the degree to which participants sought for and brought additional or different information to their prediction. The scale items were also influenced by the work of Jackson and Joshi 2011.

Differences in interpretation is defined as participants actually using or employing different information and thinking to make their individual predictions. It is measured by a nine item scale adapted from studies by Strutton and Lumpkin 1994; Moorman 1995; Deshpande and Zaltman 1982; Chaston, Badger, and Sadler-Smith 2000; Day and Nedungadi 1994; Cheng, Luckett, and Schulz 2003; and Rindfleisch and Moorman 2001. These scales assess the degree to which participants use their different information and thinking to make an accurate prediction. The scales were also influenced by the work of Jaworski, and MacInnis 1989; Surowiecki 2005; Watson, Kumar, and Michaelsen 1993; and Jackson, May, and Whitney 1995.

Use of shared information is defined as participants using the information shared in the system to make or update their predictions. It is measured by a seven item scale adapted from studies by Slater and Narver 2000; Li and Calantone 1998; Hurley and Hult 1998; Tjosvold and Poon 1998; Mohammed and Ringseis 2001; and Sethi 2000. These scales assess the degree to which participants use the information shared in the system to make or update their prediction. The scales were also influenced by the work of Moorman 1995 and Jackson, May, and Whitney 1995.

Knowledge heterogeneity is defined as participants having different perspectives, information, experiences, skills, and abilities to bring to a prediction as a result of being different from each other. It is measured by a seven item scale adapted from studies by Rindfleisch and Moorman 2001; Deshpande and Zaltman 1982; Moorman and Miner 1997; and Pelled, Eisenhardt, and Xin 1999. These scales assess the different knowledge and opinions people bring to a prediction because they are different from each other. The scales were also influenced by the work of Jackson, May, and Whitney 1995; Jackson and Joshi 2011; and Jackson 1996.

Forecast independence is defined as participants being willing and able to share individual information and opinions in their predictions because they are free from organizational influence and consequences and they can chose their own sources and approach. It is measured by a seven item scale adapted from studies by Sparks 1994; Hartline and Ferrell 1996; Deshpande and Zaltman 1982; Chaston, Badger, and Sadler-Smith 2000; and Tjosvold and Poon 1998. These scales assess participants' willingness and ability to source and share individual information and share opinions due to perceived freedom from organizational influence and consequences. The scales were also influenced by the work of Hurley and Hult 1998; Sinkula, Baker, and Noordewier 1997; and Baker and Sinkula 1999.

Incremental incentive is defined as extrinsic or intrinsic rewards that provide motivation for participants to invest time and effort into searching for information and making an accurate prediction. It is measured by a nine item scale adapted from studies by Beer and Katz 2003; and Ingram and Bellenger 1983.   These scales assess the motivation that extrinsic and intrinsic rewards provide to participants to invest time and effort into searching for information and making an accurate prediction. The scales were also influenced by the work of Chiang and Birtch 2005 and Abbey and Dickson 1983.

The scales reviewed from the literature most frequently used five or seven point scales; therefore, a 7-point Likert scale is chosen for all of the scales in this study to provide more variability in final data. Scale items were rotated within the questions for each construct to eliminate any order bias.

Validation

Pre-Analysis Data Screening

The final sample size of the post survey is 103 respondents which meets the minimum requirements for factor analysis (Kline 2011; Hair et al.2012). There are 49 items or indicator variables intended to measure six constructs. The following analyses and discussions refer to scale items by their survey codes (e.g. Q3_1); Appendix C shows all of the scale items with these codes and the actual question statements. Due to Qualtrics survey programming and controls, there were no outliers or missing values. All variables have significant Kolomogorov-Smirnov test statistics; therefore no variables are perfectly normally distributed (Kline 2011; Tabachnick and Fidell 2007). This is due to many of the variables being censored variables (Kline 2011). Examination of skewness and kurtosis statistics (see Appendix D) indicates that most variables fall within the accepted range of +/- 1.0, with most others (six) falling within the range +/- 1.5 which will be considered acceptable for this analysis (Mertler and Vannatta 2005). Five items from the Q8_Independence scale display severe negative skewness and severe positive kurtosis (leptokurtic or peakedness) so they will require transformation. Almost all items in this scale suffer from this problem so all of the items in the scale should be transformed. A SQRT transformation produced skewness and kurtosis scores within the range of +/- 1.0. (Tabachnick and Fidell 2007).

Exploratory Factor Analysis

All 49 variables were subjected to a combined exploratory factor analysis with principle components extraction and varimax rotation. Examination of eiganvalues greater than 1.0 and of the scree plots, displayed on Table 31 and Figure 6, indicate a nine factor solution. This solution accounts for 75% of total variance with communalities ranging from 0.493 to 0.874 and only one communality value below 0.5 (Hair et al. 2010). There were no scores out of bounds (>1 or <0). The Kaiser-Meyer-Olkin (KMO) of sampling adequacy is 0.76, indicating a factor analysis is feasible with this data and variables (Tabachnick and Fidell 2007). According to practical significance criteria, for a sample size of 100 or larger, factor loadings exceeding 0.7 are considered indicative of well-defined structure and are the goal of factor analysis (Hair et al. 2010). According to statistical significance criteria, for a sample size of 100, only factor loadings exceeding 0.55 and above are significant (Hair et al. 2010). According to these criteria, the following preliminary assessments are made regarding the scales based on data tabulated in Appendix E.

Four out of the six model constructs emerge clearly as factors; their respective items have high loadings onto only one factor; there are very few scores below acceptable levels, and there is very little cross-loading loading onto them (Kline 2011; Hair et al. 2010; Tabachnick and Fidell 2007). Items for Q3_Heterogeneity, Q4_Acquisition, Q5_SharedInfo and Q8_Independence loaded, without exception, on corresponding factors and had many factor loadings of over 0.8.

Table 31. Factor Analysis Total Variance Explained

	Initial Eigenvalues		
Component	Total	% of Variance	Cumulative %
1	12.15	24.8	24.8
2	6.64	13.5	38.3
3	4.79	9.8	48.1
4	3.38	6.9	55.0
5	3.24	6.6	61.6
6	2.26	4.6	66.2
7	1.66	3.4	69.6
8	1.28	2.6	72.2
9	1.17	2.4	74.6
10	1.00	2.0	76.6
11	0.94	1.9	78.5
12	0.88	1.8	80.3

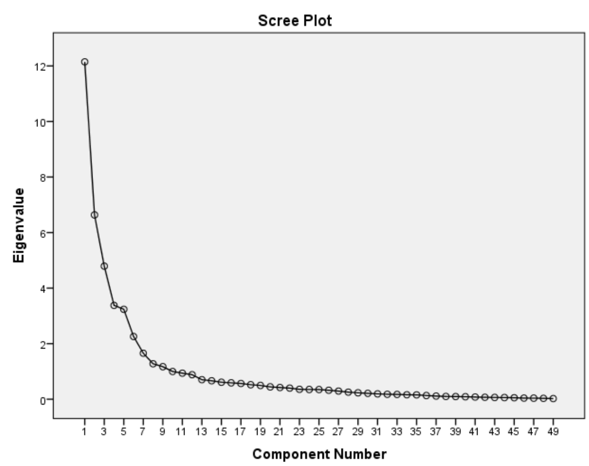

Figure 6. Factor Analysis Scree Plot
Extraction Method: Principal Component Analysis

This is a good indication for unidimensionality and scale integrity for these constructs. Most items for Q6_Interpretation loaded onto a unique factor, but a few items load more strongly onto Q4_Acquisition. This blurring of Interpretation and Acquisition will be monitored as a problem proceeding with the analysis. Items for Q7_Incentives load onto three separate factors corresponding to being a top performer, participating in an interesting process, and winning a prize. This raises a serious issue with unidimensionality. Later analysis should consider selecting the most face valid dimension of the incentive scale and retain only the variables that load onto it; also emphasize the items most supported from the literature (top performer and prize).

Examining the Pearson correlation matrix produces the following preliminary observations of validity. These will be tested further in SEM analysis that follows. The constructs Q3_Diversity, Q4_Acquisition, Q5_SharedInfo , and Q8_Independence all display preliminary convergent validity with the majority of their variables having within-factor inter-item correlations of more than 0.50, many with higher values (Kline 2011). Each construct has a couple of items that display inter-item correlations of less than 0.50, and these will be monitored corresponding with other analyses as candidates for elimination. Corresponding with the factor analysis, the constructs Q6_Interpretation and Q7_Incentive display some issues with preliminary convergent validity. Q6_Interpretation has four items that display inter-item correlations of less than 0.50, which will be monitored corresponding with other analyses as candidates for elimination. Q7_Incentive has several items that display inter-item correlations of less than 0.50, which can be attributed to the unidimensionality issue identified in the factor analysis. Combining two factors' items, eliminating variables for the third, and eliminating other low value variables may address this issue. There are no significant cross-factor inter-item correlations of more than 0.70 which indicates preliminary divergent validity (Kline 2011). The factors Q4_Acquisition and Q6_Interpretation do share some cross-factor inter-item correlations in the range of 0.5 to 0.66, but these two factors are highly related from a theoretical standpoint being the acquisition and use of additional and different information. These findings will guide further and more specific analysis of the scales and items and possible changes to them.

Scale Purification

In order to optimize the measurement model, individual scales were subjected to two rounds of factor analysis and reliability analysis in SPSS. In the first round of analysis, the full set of scales is analyzed, and based on various pertinent performance scores, 19 poorly fitting scale items will be deleted from the measurement model. In the second round of analysis the reduced set of scales is analyzed, and based on a similar assessment of performance scores, two more scale items will be removed.

Factor & Reliability Analysis for Individual Scales

The following sections and tables summarize analysis and results for two rounds of factor analysis based on a principle components extractions and varimax rotation. The assessment criteria, threshold levels, and decisions for the following factor analyses are based on information and guidelines cross-referenced from Hair et al. 2010; Kline 2011; Tabachnick and Fidell 2007; and Mertler and Vannatta 2005 in their chapters and sections covering factor analysis. Similarly, assessment criteria, threshold levels, and decisions for the following reliability analyses are based on information and guidelines cross referenced from Hair et al. 2010; Kline 2011; and Diamantopoulos and Siguaw 2000.

The individual factor analysis for the Q3_Heterogeneity scale extracted only one component, indicating a clear single factor solution. From Table 32, the sampling adequacy, as measured by Kaiser-Meyer-Olkin (KMO), is 0.87 which indicates a satisfactory factor analysis to proceed (greater than 0.5).

Table 32. Individual Scale Analysis: Heterogeneity

Scale / Items	Factor Loadings Comp1	Comp2	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Q3_1	0.76	N/A	0.58	71.28	0.87	0.69	0.93
Q3_2	0.85		0.72			0.79	
Q3_3	0.84		0.70			0.77	
Q3_4	0.89		0.79			0.84	
Q3_5	0.87		0.76			0.82	
Q3_6	0.86		0.73			0.80	
Q3_7	0.84		0.70			0.77	

The total variance explained is 71.3%. For a sample size of 100, factor loadings of at least 0.55 are needed for significance and loadings exceeding 0.70 are considered indicative of a well-defined measurement structure (Hair et al. 2010). Factor loadings for the heterogeneity scale range from 0.76 to 0.89 with one of seven items (Q3_1) having a loading below 0.8. Communalities of at least 0.50 are necessary for scale items to be sufficiently explained by their underlying factor. Communalities for the heterogeneity scale range from 0.58 to 0.79 with one of seven items (Q3_1) having a value near 0.5. The lower performing item (Q3_1) will be considered a candidate for deletion in order to achieve improved scale parsimony and item to case ratio. The reliability analysis for the

Q3_Heterogeneity scale has a coefficient alpha (Cronbach's alpha) of 0.93. This value is greater than 0.70, the minimum value necessary for sufficient scale consistency. Item-total correlations exceeding 0.7 indicate sufficient correlation between individual items and their scale. The item-total correlations for the Q3_Heterogeneity scale range from 0.69 to 0.84 with one of seven items (Q3_1) below 0.7. The lower performing item (Q3_1) will be considered a candidate for deletion in order to achieve improved scale parsimony and item to case ratio. This will reduce the number of scale items for Q3_Heterogeneity from seven to six.

The factor analysis for the Q4_Acquisition scale extracted only one component, indicating a clear single factor solution. From Table 33, sampling adequacy (KMO) is 0.89 and total variance explained is 64% indicating a satisfactory factor analysis to proceed. Factor loadings for the acquisition scale range from 0.66 to 0.87 with four of ten below 0.8 (Q4_5, Q4_8, Q4_9, and Q4_10).

Table 33. Individual Scale Analysis: Acquisition

Scale / Items	Factor Loadings Comp1	Comp2	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Q4_1	0.87	N/A	0.76	63.95	0.89	0.83	0.93
Q4_2	0.85		0.71			0.79	
Q4_3	0.84		0.71			0.79	
Q4_4	0.87		0.76			0.83	
Q4_5	0.76		0.58			0.70	
Q4_6	0.83		0.68			0.77	
Q4_7	0.83		0.68			0.77	
Q4_8	0.68		0.46			0.61	
Q4_9	0.66		0.44			0.60	
Q4_10	0.78		0.61			0.73	

Communalities for the acquisition scale range from 0.44 to 0.76 with two of ten items (Q4_8 and Q4_9) having values below 0.5. The lower performing items (Q4_5, Q4_8, Q4_9, and Q4_10) will be considered candidates for deletion. The reliability analysis for the acquisition scale has a sufficient coefficient alpha of 0.93. Item-total correlations for the acquisition scale range from 0.60 to 0.83 with two of seven items (Q4_8 and Q4_9) below 0.7. The lower performing items (Q4_5, Q4_8, Q4_9, and Q4_10) will be considered candidates for deletion in order to achieve improved scale parsimony and item to case ratio. This will reduce the number of scale items for Q4_Acquisition from ten to six.

The factor analysis for the Q5_SharedInfo scale extracted only one component, indicating a clear single factor solution. From Table 34, sampling adequacy (KMO) is 0.83 and total variance explained is 61.9% indicating a satisfactory factor analysis to proceed. Factor loadings for the sharedinfo scale range from 0.52 to 0.88 with two of seven below 0.8 (Q5_1and Q5_7).

Table 34. Individual Scale Analysis: SharedInfo

Scale / Items	Factor Loadings Comp1	Comp2	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Q5_1	0.74	N/A	0.54	61.93	0.83	0.63	0.89
Q5_2	0.85		0.72			0.78	
Q5_3	0.83		0.69			0.75	
Q5_4	0.81		0.66			0.74	
Q5_5	0.82		0.67			0.72	
Q5_6	0.88		0.78			0.82	
Q5_7	0.52		0.27			0.42	

Communalities for the sharedinfo scale range from 0.27 to 0.78 with two of seven items (Q5_1and Q5_7) having values near or below 0.5. The item Q5_7 also had a cross loading issue in the preliminary exploratory factor analysis. The lower performing items (Q5_1and Q5_7) will be considered candidates for deletion. The reliability analysis for the sharedinfo scale has a sufficient coefficient alpha of 0.89. Item-total correlations for the sharedinfo scale range from 0.42 to 0.82 with three of seven items (Q5_1, Q5_5, and Q5_7) near or below 0.7. The lower performing items (Q5_1and Q5_7) will be considered candidates for deletion which will reduce the number of scale items for Q5_SharedInfo from seven to five.

The eigenvalues and scree plot from for the Q6_Interpretation scale factor analysis indicate a possible two factor solution. From Table 35, the first component (six items) represents a use of data dimension and the second component (three items) represents a different perspective/interpretation dimension.

Table 35. Individual Scale Analysis: Interpretation

Scale / Items	Factor Loadings Comp1	Comp2	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Q6_1	0.75	0.29	0.64	59.16	0.86	0.66	0.91
Q6_2	0.66	0.54	0.72			0.79	
Q6_3	0.31	0.87	0.86			0.76	
Q6_4	0.25	0.87	0.82			0.71	
Q6_5	0.27	0.87	0.83			0.72	
Q6_6	0.72	0.46	0.73			0.78	
Q6_7	0.63	0.38	0.54			0.65	
Q6_8	0.86	0.04	0.74			0.57	
Q6_9	0.65	0.33	0.53			0.63	

Many of the items of the first component correspond to cross loading issues with Q4_Acquisition in the preliminary exploratory factor analysis; they share a common dimension of getting and using new information. The three items of the second component (Q6_3, Q6_4, and Q6_5) better reflect the true theoretical construct of differences in interpretation, so these items will be retained. Five of the six items of the first component will be deleted to achieve clarity and unidimensionality and a scale that aligns more closely with the theoretical construct. Factor loadings for the retained items of the second component are all approximately 0.87. Communalities for the retained items range from 0.82 to 0.86. The reliability analysis for the entire interpretation scale has a coefficient alpha of 0.91. Item-total correlations for the interpretation scale range from 0.57 to 0.79 with four of nine items (Q6_1, Q6_7, Q6_8, and Q6_9) below 0.7. All of these items correspond with the first component to be deleted. One item from first component (Q6_6) has a high item-total correlation and is theoretically consistent with items in the retained second component. This item will be retained for further analysis. These recommendations will reduce the number of scale items for Q6_Interpretation from nine to four.

The eigenvalues and scree plot for the Q7_Incentive scale factor analysis indicate a possible two factor solution. From Table 36, the first component (five items) represents a dimension of winning a contest or prize and the second component (four items) represents a dimension of participating in a novel exercise.

Table 36. Individual Scale Analysis: Incentives

Scale / Items	Factor Loadings Comp1	Comp2	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Q7_1	0.81	0.02	0.66	46.92	0.77	0.55	0.86
Q7_2	0.83	0.16	0.72			0.65	
Q7_3	(0.10)	0.88	0.78			0.36	
Q7_4	0.81	0.17	0.69			0.64	
Q7_5	0.12	0.90	0.83			0.56	
Q7_6	0.71	0.08	0.50			0.50	
Q7_7	0.35	0.73	0.66			0.63	
Q7_8	0.62	0.46	0.59			0.67	
Q7_9	0.49	0.58	0.58			0.64	

These two dimensions correspond to cross loading issues in the preliminary exploratory factor analysis. The five items of the first component (Q7_1, Q7_2, Q7_4, Q7_6, and Q7_8) better reflect the true theoretical construct of competing for and winning extrinsic rewards, so these items will be retained. The four items of the second component will be deleted to achieve clarity and unidimensionality and a scale that aligns more closely with the theoretical construct. Factor loadings for the retained items of the first component range from 0.62 to 0.83 with two of the items (Q7_6 and Q7_8) having loadings below 0.8. Communalities for the retained items range from 0.50 to 0.83 with two of the items (Q7_6 and Q7_8) having values near or below 0.5. Due to their importance to the true theoretical construct, items Q7_6 and Q7_8 will be retained for further analysis and possible deletion at a later stage. The reliability analysis for the interpretation scale has a coefficient alpha of 0.86. Item-total correlations for the interpretation scale range from 0.36 to 0.67 with all nine items below 0.7. This raises serious issues with scale consistency and reliability. In order to retain the scale for further analysis, a temporary threshold of 0.6 will be used here resulting in four out of nine items falling below 0.6.

Two of these items (Q7_3 and Q7_5) correspond to the second component recommended for deletion from the factor analysis. The other two of these items (Q7_1 and Q7_6) correspond to the first component recommended retention – these two items had acceptable factor loadings so will be recommended retention for further analysis. These recommendations will reduce the number of scale items for Q7_Incentive from nine to five that will need to be monitored closely in the latter stages of analysis.

The factor analysis for the Q8_Independence scale extracted only one component, indicating a clear single factor solution. From Table 37, sampling adequacy (KMO) is 0.88 and total variance explained is 69.7% indicating a satisfactory factor analysis to proceed. Factor loadings for the Independence scale range from 0.68 to 0.93 with three of seven near or below 0.8 (Q8_1, Q8_2, and Q8_7).

Table 37. Individual Scale Analysis: Independence

Scale /	Factor Loadings			Variance		Item-Total	Cronbach's
Items	Comp1	Comp2	Comm	Explained	KMO	Correlations	Alpha
Q8_1	0.68	N/A	0.46	69.68	0.88	0.60	0.92
Q8_2	0.77		0.59			0.71	
Q8_3	0.81		0.65			0.72	
Q8_4	0.91		0.83			0.85	
Q8_5	0.93		0.87			0.88	
Q8_6	0.92		0.84			0.86	
Q8_7	0.80		0.63			0.71	

Communalities for the independence scale range from 0.46 to 0.87 with one of seven items (Q8_1) below 0.5. The lower performing items (Q8_1, Q8_2, and Q8_7) will be considered candidates for deletion. The reliability analysis for the independence scale has a sufficient coefficient alpha of 0.92. Item-total correlations for the independence scale range from 0.60 to 0.88 with two of seven items (Q8_1and Q8_2) near or below 0.7. The lower performing items (Q8_1, Q8_2, and Q8_7) will be considered candidates for deletion which will reduce the number of scale items for Q8_ Independence from seven to four.

Respecified Factor & Reliability Scale Analysis

Based on the first round of scale analysis and review, the factor model was respecified with 19 of 49 scale items recommended for deletion, leaving 30 for second round factor and reliability analyses (Hair et al. 2010). Table 38, shows the results of the trimmed set of scales, which in most cases, indicate improved performance measures as summarized below.

For the reduced Q3_Heterogeneity scale, the KMO measure decreased slightly to 0.84 and total variance explained increased slightly to 74.4%. Factor loadings generally improved to a range from 0.83 to 0.90 and communality values improved to a range of 0.71 to 0.81. Coefficient alpha remained the same at 0.93 and item-total correlations improved to a range from 0.77 to 0.85. These results will retain the six scale items for Q3_Heterogeneity.

For the reduced Q4_Acquisition scale, the KMO measure decreased slightly to 0.86 and total variance explained increased to 71.2%. Factor loadings improved to a range from 0.79 to 0.89 (with one of seven below 0.8) and communality values improved to a range from 0.62 to 0.80. Coefficient alpha remained the same at 0.93 and item-total correlations improved to a range from 0.72 to 0.85.

Table 38. Respecified Factor & Reliability Scale Analysis

Scale/ Items	Factor Loadings	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Heterogeneity			74.42	0.84		0.93
Q3_2	0.84	0.71			0.77	
Q3_3	0.82	0.68			0.75	
Q3_4	0.90	0.81			0.85	
Q3_5	0.90	0.80			0.84	
Q3_6	0.87	0.76			0.81	
Q3_7	0.85	0.71			0.77	
Acquisition			71.77	0.86		0.93
Q4_1	0.89	0.80			0.85	
Q4_2	0.88	0.77			0.82	
Q4_3	0.84	0.71			0.78	
Q4_4	0.86	0.74			0.81	
Q4_5	0.79	0.62			0.72	
Q4_6	0.84	0.70			0.77	
Q4_7	0.82	0.68			0.75	
SharedInfo			72.35	0.77		0.90
Q5_2	0.86	0.74			0.77	
Q5_3	0.83	0.69			0.74	
Q5_4	0.83	0.69			0.73	
Q5_5	0.82	0.68			0.72	
Q5_6	0.90	0.82			0.84	
Interpretation			75.51	0.82		0.89
Q6_3	0.92	0.84			0.84	
Q6_4	0.90	0.80			0.80	
Q6_5	0.89	0.80			0.80	
Q6_6	0.76	0.57			0.61	

Table 38. (continued)

Scale/ Items	Factor Loadings	Comm	Variance Explained	KMO	Item-Total Correlations	Cronbach's Alpha
Incentives			61.34	0.72		0.84
Q7_1	0.81	0.65			0.68	
Q7_2	0.85	0.72			0.73	
Q7_4	0.83	0.69			0.71	
Q7_6	0.71	0.51			0.56	
Q7_8	0.70	0.50			0.55	
Independence			84.52	0.83		0.94
Q8_3	0.84	0.70			0.73	
Q8_4	0.95	0.89			0.89	
Q8_5	0.94	0.89			0.89	
Q8_6	0.95	0.89			0.90	

Based on these results, one additional item (Q4_5) will be deleted for scale parsimony. This will reduce the number of scale items for Q4_Acquisition further from six to five.

For the reduced Q5_SharedInfo scale, the KMO measure decreased to 0.77 and total variance explained increased significantly to 72.4%. Factor loadings improved to a range from 0.82 to 0.90 and communality values improved to a range from 0.69 to 0.82. Coefficient alpha increased marginally to 0.90 and item-total correlations improved to a range from 0.72 to 0.84. These results will retain the five scale items for Q5_SharedInfo.

The factor analysis for the reduced Q6_Interpretation scale extracted only one component, now indicating a clear single factor solution. The KMO measure decreased to 0.82 and total variance explained increased significantly to 75.5%. Factor loadings improved to a range from 0.76 to .92 (with one of four below 0.8) and communality values improved to a range from 0.57 to 0.84 with same item (Q6_6) near a value of 0.5. Coefficient alpha decreased slightly to 0.89 but this an acceptable trade off to reduce the number of scale items. Item-total correlations improved to a range from 0.61 to 0.84 with one item (Q6_6) below 0.7. In order to meet requirements for at least four items for a small sample (Kline 2011), item Q6_6 will be retained and Q6_Interpretation will remain at four scale items.

The factor analysis for the reduced Q7_Incentive scale extracted only one component, now indicating a clear single factor solution focused on extrinsic rewards. The KMO measure decreased slightly to 0.72 and total variance explained increased significantly to 61.3%. Factor loadings improved to a range from 0.70 to .85 with two of five items (Q7_6 and Q7_8) below 0.8. Communality values improved to a range from 0.50 to 0.72 with the same two items at or near a value of 0.5. Coefficient alpha decreased slightly to 0.84. Item-total correlations improved to a range from 0.55 to 0.73 with three items (Q7_1 Q7_6, and Q7_8) below 0.7. In order to meet requirements for at least four items for a small sample (Kline 2011), the two highest scoring items below 0.7 will be retained. Based on this, the number of scale items for Q7_Incentive will be reduced from five to four.

For the reduced Q8_Independence scale, the KMO measure decreased to 0.83 and total variance explained increased significantly to 84.5%. Factor loadings improved to a range from 0.84 to 0.95 and communality values improved to a range from 0.70 to 0.89. Coefficient alpha increased to 0.94 and item-total correlations improved to a range from 0.73 to 0.90. These results will retain the four scale items for Q8_Independence.

Based on this second round of analysis, the following observations can be made:

- the number of items has decreased further from 30 to 29 which improves the cases-to-items ratio to 3.7,

- all scales have achieved unidemensionality,
- all but one KMO decreased slightly corresponding with a reduction in items, all are acceptable with the lowest value at 0.72
- all variance explained values increased (some of them significantly), values now range from 61.3% to 84.5%,
- almost every factor loading increased, all but two factor loadings now exceed 0.8, those below 0.8 are acceptable (lowest factor loading exceeds 0.7)
- almost every communality value increased and all but one value now exceed 0.5
- four out of six scales maintain or increase their coefficient alphas, the two coefficient alpha declines are very small and acceptable, all coefficient alphas exceed 0.8
- almost every item-total correlation increased, all but three item-total correlations now exceed 0.7, and those below 0.7 are acceptable (lowest item-total correlation exceeds 0.5).

At this stage of the analysis, scales are reduced and holding together rather strongly with high performance values, their theoretical integrity has been improved and clarified and the cases-to-items ratio has been improved. These scales will proceed to confirmatory analysis within the structural equation modeling stage this follows.

Analysis and Results

Pre-analysis data screening and two rounds of factor analysis and reliability analysis reduced the measurement model from 49 to 29 scale items. The next step in the analysis and assessment of the measurement model is to subject the proposed model to confirmatory factor analysis within a structural equation modeling analysis.

Analytical Approach

When working with structural equation modeling in marketing research, there are two dominant SEM techniques available: covariance-based CB-SEM and variance-based partial least squares PLS-SEM. In 1982, Wold introduced PLS-SEM as an alternative to CB-SEM due to concerns that CB-SEM's informational and distributional requirements and specification of relationships were unrealistic for empirical research and that the emphasis of CB-SEM was on description and estimation over prediction. Since then, application of PLS-SEM has expanded in business, education, and social sciences research and practice (Hair et al. 2010, Hair, Ringle, and Sarstedt 2011, Hair et al. 2012). Kline (2011) recommends and describes PLS path modeling for situations when prediction is emphasized over theory testing and it is difficult to meet the sample and model requirements of traditional CB-SEM. PLS-SEM has been increasingly applied in marketing. An examination of leading marketing journals over the 10 year period 2003-2012 reveals 49 articles using PLS analysis with the following breakdown: Journal of Marketing 17, Journal of Marketing Research 5, Journal of the Academy of Marketing Science 17, and Journal of Product Innovation Management 10. PLS-SEM is a causal modeling approach with the primary objective of evaluating data quality of the measurement model and maximizing explained variance in the dependent constructs. The modeling procedure is called partial because the iterative PLS-SEM algorithm estimates the coefficients for the partial ordinary least squares regression models in the measurement models and then the structural model. The PLS-SEM algorithm first optimizes measurement model parameters and then, in a second step, estimates the path coefficients in the structural model. Estimating models via a series of OLS regressions, PLS-SEM relaxes the assumption of multivariate normality, has minimum demands regarding sample size, and generally achieves high levels of statistical power. PLS-SEM structural equation models with good measurement properties have generally been found to achieve comparable results to CB-SEM (Hair et al. 2010; Hair, Ringle, and Sarstedt 2011).

The focus of PLS-SEM is on prediction as it maximizes the explained variance of the endogenous latent variables. In contrast, the focus of CB-SEM is on theory testing as it estimates model parameters to minimize the discrepancy between the estimated and sample covariance matrices and explains the relationships between items. Through an iterative sequence of ordinary least squares (OLS) regressions, PLS-SEM estimates constructs as exact linear combinations of observed indicator variables and estimates partial model relationships. In PLS, the loadings of the measured variables for exogenous constructs are based on their prediction of the endogenous measured variables (i.e. their contribution to the path estimates). In contrast, the emphasis in CB-SEM is on construct validity, shared variance among measured variables on the same construct irrespective of the other constructs in the model (Hair et al. 2010; Kline 2011; and Hair et al. 2012).

The advantages of PLS-SEM are related to its prediction of an outcome variable, exploratory ability, and robustness. Its limited-information OLS based estimation algorithm is not as demanding as full-information maximum likelihood (ML) based estimation in CB-SEM. As a result it can work with wider range of sample sizes (does not require large sample sizes), it has less restrictive assumptions about the data (normal distributions are not required), it can work with constructs with fewer items (including single item measures), and it avoids many SEM specification/identification problems associated with complex models (Hair et al. 2010 and Kline 2011). The disadvantages of PLS-SEM are the lack of global measure of goodness of model fit, PLS significance testing requires bootstrapping techniques, and parameter estimates are not optimal regarding bias and consistency (referred to as PLS-SEM bias). Due to less stringent tests of the measurement model, researchers must also be confident about the quality of their measurement model (Hair et al. 2010; Hair, Ringle, and Sarstedt 2011; and Hair et al. 2012). According to Hair et al. (2011) and Hair et al. (2012), researchers should choose between the two SEM alternatives based on the following criteria.

Researchers should to use variance based PLS-SEM under the following conditions.

- CB-SEM assumptions cannot be met,
- The research objective is prediction or theory development,
- The research is exploratory,
- It is a situation where theory is less developed,
- The goal is predicting or identifying key driver constructs,
- The sample size is relatively low,
- The data are to some extent nonnormal or highly skewed (common with empirical data),
- The model is more complex or has a large number of factors.

Researchers should to use covariance based CB-SEM under the following conditions.

- The data and model meet CB-SEM assumptions exactly,
- The research objective is theory testing and confirmation of structural relationships,

- It is a situation where prior theory is strong and further testing and confirmation are the goals,
- The goal is comparison of alternative theories.

Based on the purpose of the present study and the nature of the data and model, a variance based PLS-SEM analysis is most appropriate. The match between PLS attributes and the parameters of this study's data is strong both of which support the use of PLS as the SEM approach for the analysis and assessment of the measurement model and structural model: i) the purpose of this study is to explore and combine various explanations of prediction markets' accuracy and develop an explanatory theory; ii) the focus of the analysis is to identify key constructs that can predict forecast accuracy; and iii) the sample size is relatively low and the observed data are highly skewed. In addition, the proposed model is a focused model for which PLS-SEM is particularly suited (a small number of endogenous variables explained by a large number of exogenous latent variables). The measurement model is exactly in line with PLS-SEM practice as observed in the marketing literature: the average number of indicators per construct is four and the average number of indicators in the total path model is 30 (Kline 2011; Hair et al. 2012). The sample size of 103 cases meets the minimum PLS-SEM threshold of 10 times the largest number of structural paths directed at a particular latent construct in the structural model (Hair, Ringle, and Sarstedt 2011). Finally, the measurement model has undergone rigorous scale analysis and purification to meet the requirement of a quality measurement model in order for PLS-SEM to yield acceptable parameter estimates with a smaller sample size (Hair et al. 2012). The 103 cases from the post survey and Smart-PLS 2.0 partial least squares modeling approach will be used for this study (Ringle, Wende, and Will 2005).

Results

PLS-SEM assessment typically follows a two-step process that involves separate assessments of the measurement model and the structural model. The first step is to examine the measurement model validity and reliability according to criteria associated with reflective measurement model specification. If the measures are shown to be adequate, the second step involves estimating and assessing the structural model. In PLS analysis, the measurement model is referred to as the inner model, the structural model as the outer model, and reflective coefficients for the indicators as outer loadings (Hair, Ringle, and Sarstedt 2011).

Measurement Model Assessment

The assessment of a PLS reflective measurement model addresses internal consistency reliability, indicator reliability, convergent validity, and discriminant validity (Hair, Ringle, and Sarstedt 2011). Table 39 presents the initial round of measurement model quality statistics. The order of constructs in the tables is based on the order of questions in the Qualtrics survey; designed to minimize the influence of question exposure based on early and later responses in the survey sequence.

Construct reliability assessment in PLS focuses on composite reliability as an estimate of a construct's internal consistency. In PLS, composite reliability is used rather than Cronbach's Alpha because the former does not assume all indicators are equally weighted, which is inherent in PLS treatment of indicators.

Table 39. Measurement Model Quality Criteria

Construct	AVE	Composite Reliability	Communality
Q4_Acquisition	0.740	0.945	0.740
Q5_SharedInfo	0.565	0.861	0.565
Q3_Heterogeneity	0.739	0.944	0.739
Q7_Incentives	0.665	0.888	0.665
Q8_Independence	0.129	0.131	0.129
Q6_Interpretation	0.676	0.890	0.676

Composite reliability values of 0.60 to 0.70 in exploratory research and values from 0.70 to 0.90 in more advanced stages of research are regarded as satisfactory, and values below 0.60 indicate a lack of reliability (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). Composite reliability statistics for this measurement model range from 0.131 to 0.945 with one value being below the threshold of 0.6. The value of 0.131 for the construct Q8_Independence is far below any value that can support acceptable internal consistency; this construct should be a candidate for elimination during model refinement. The remaining constructs all have strong composite reliability scores indicating internal consistency. In addition, each indicator's reliability needs to be taken into account by ensuring that each indicator's absolute standardized loading is higher than 0.70 (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). An examination of Appendix A indicates that seven scale items exhibit loadings of less than 0.7 with their respective latent constructs: Q5_3 (0.505) and Q5_4 (0.603); Q6_6 (0.587); and Q8_3 (-0.323), Q8_4 (0.423), Q8_5 (0.448), and Q8_6 (0.177). Items scores for Q5_3 and Q5_4 of the Q5_SharedInfo scale are within the range of 0.6 to 0.7 which is sufficient reliability to be retained if items are important to content validity (Hair, Ringle, and

Sarstedt 2011). Item Q6_6 of the Q6_Interpretation scale is also within the 0.6 to 0.7 range; however, this item displayed poor performance in the preliminary factor and reliability analyses and should be considered a candidate for deletion. All of the items loadings for the Q8_Independence scale fell below 0.5 consistent with the low composite reliability value, and further supporting the removal of this scale from the model.

Convergent validity assessment is based the average variance extracted (AVE). An AVE value of 0.50 and higher indicates a sufficient degree of convergent validity, meaning that the latent variable explains more than half of its indicators' variance (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). AVE values for this measurement model range from 0.129 to 0.740 indicating sufficient convergent validity for all latent constructs except the Q8_Independence scale (0.129) already identified for deletion.

Discriminant validity is typically assessed by two measures, the Fornell-Larcker criterion and cross loadings. The Fornell–Larcker criterion assesses whether a latent construct shares more variance with its assigned indicators than with another latent variable in the structural model (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). In statistical terms, the AVE of each latent construct should be greater than the latent construct's highest squared correlation with any other latent construct. Comparing AVE values against the squared correlations in Table 40 shows all construct AVE values as greater than their highest squared correlation with any other construct.

Table 40. Latent Construct Squared Correlations (Fornell-Larcker criterion)

	Q4_Acq	Q5_Diss	Q3_Div	Q7_Inc	Q8_Ind	Q6_Int
Q4_Acquisition	1.000					
Q5_SharedInfo	0.038	1.000				
Q3_Heterogeneity	0.004	0.000	1.000			
Q7_Incentives	0.057	0.006	0.003	1.000		
Q8_Independence	0.025	0.002	0.020	0.003	1.000	
Q6_Interpretation	0.151	0.050	0.077	0.015	0.045	1.000

For the second criterion of discriminant validity, an indicator's loading with its associated latent construct should be higher than its loadings with all the remaining constructs (i.e. cross loadings) (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). An examination of Appendix F indicates one Q6_Interpretation scale item (Q6_6) as loading higher on the Q4_Acquisition scale. This result, combined with its poor indicator reliability value should confirm the deletion of this item from the measurement model.

Based on this initial round of analysis and review of the measurement model, one latent construct (Q8_Independence) and one scale item (Q6_6) should be removed prior to assessing the structural model. In a second PLS run of the measurement model, the following observations can be made from Table 41: i) composite reliability statistics range from 0.861 to 0.945, ii) AVE values range from 0.665 to 0.786, and iii) communalities range from 0.565 to 0.786.

Table 41. Respecified Measurement Model Quality Criteria

	AVE	Composite Reliability	Communality
Q4_Acquisition	0.740	0.945	0.740
Q5_SharedInfo	0.565	0.861	0.565
Q3_Heterogeneity	0.739	0.944	0.739
Q7_Incentives	0.665	0.888	0.665
Q6_Interpretation	0.786	0.916	0.786

Table 42 shows that item loadings range from 0.505 to 0.992; inspection of the full data table also finds that there are no items cross loaded onto other scales. Table 43, indicates that all of the items are also significant. T-Statistics were produced through a bootstrapping procedure specified with no missing values, 5000 samples, and 103 cases. Standard practice in PLS is to run at least 5000 samples using the same number of cases as the study sample (Hair, Ringle, and Sarstedt 2011 and Hair et al. 2012). Based on these results, it can be concluded that the measurement model meets or exceeds all requirements for reliability and validity in the PLS-SEM methodology. This is an important and necessary achievement prior to proceeding to structural model analysis given the less stringent demands of PLS compared to covariance based SEM. If a measurement model standard is achieved, the results from PLS and CB SEM structural models can often be comparable (Hair et al. 2010 and Hair, Ringle, and Sarstedt 2011).

Table 42. Measurement Model Outer Loadings

	Acq	Diss	Het	Inc	Int
Q3_2			0.860		
Q3_3			0.844		
Q3_4			0.917		
Q3_5			0.894		
Q3_6			0.838		
Q3_7			0.801		
Q4_1	0.890				
Q4_2	0.883				
Q4_3	0.860				
Q4_4	0.869				
Q4_6	0.850				
Q4_7	0.807				
Q5_2		0.811			
Q5_3		0.505			
Q5_4		0.603			
Q5_5		0.781			
Q5_6		0.970			
Q6_3					0.830
Q6_4					0.827
Q6_5					0.992
Q7_1				0.829	
Q7_2				0.847	
Q7_4				0.842	
Q7_6				0.739	

Table 43. Outer Model T-Statistics

	Acq	Diss	Het	Inc	Int
Q3_2			4.49		
Q3_3			4.50		
Q3_4			5.07		
Q3_5			4.78		
Q3_6			4.15		
Q3_7			3.70		
Q4_1	6.28				
Q4_2	6.36				
Q4_3	5.68				
Q4_4	5.95				
Q4_6	5.87				
Q4_7	4.71				
Q5_2		3.91			
Q5_3		2.25			
Q5_4		2.58			
Q5_5		3.36			
Q5_6		4.23			
Q6_3					4.23
Q6_4					4.11
Q6_5					4.62
Q7_1				3.48	
Q7_2				3.16	
Q7_4				3.03	
Q7_6				2.82	

Structural Model Assessment

Having addressed the assessment and satisfaction of measurement model requirements, the structural model can now be assessed. From the conceptual framework depicted in Figure 1 in chapter three, the EPM design factors will serve in this analysis as the independent exogenous latent constructs and the forecast error measure (APE) as the dependent endogenous variable. Individual respondent's APE (absolute percentage error) values used as the dependent variable here are the same values used in Study I, the assessment of EPM performance. Within each record or case in the structural model analysis, individual APE values will correspond with the EPM prediction question each respondent selected and assessed in the post survey. Each respondent's unique EPM system username from Study I was appended to their completed post survey in Qualtrics. This allowed the two sets of data from the studies one and two to be combined into one file for the structural model analysis that follows. The structural model is also run in Smart-PLS 2.0 (Ringle, Wende, and Will 2005) with the following default settings as recommended by Hair et al. (2011) and Hair et al. (2012): no missing values, factor weighting scheme, data metrics of mean (0) and var (1), maximum iterations 300, abort criterion 1.0E-%, and initial weights of 1.0. The model analysis stopped (converged) after three iterations. The assessment of a PLS path structural model addresses R-Square value, constructs' predictive relevance, segment heterogeneity, and path coefficients' size and significance (Hair, Ringle, and Sarstedt 2011).

When using PLS-SEM, researchers must focus their evaluation on variance-based, non-parametric evaluation criteria to assess the inner model's quality. The primary criterion for inner model assessment is the coefficient of determination (R-

Square), which represents the amount of explained variance of each endogenous latent variable (Hair et al. 2012). In marketing research studies, R-Square values of 0.75, 0.50, and 0.25 for endogenous latent variables in the structural model can be described as substantial, moderate, or weak, respectively (Hair, Ringle, and Sarstedt 2011). The R-Square value for the respecified model is 0.103; it was 0.12 with Q8_Independence included, but this scale does not meet requirements for reliability and validity and should remain omitted.

For models based on a reflective measurement model, the structural model's predictive relevance should be assessed. Sample re-use techniques can be used to assess the model's predictive validity by means of the cross-validated redundancy measure Stone–Geisser's Q^2. To assess the models ability to adequately predict each endogenous latent construct's indicators, the procedure omits every d^{th} data point and uses the resulting estimates to predict the omitted part. If an endogenous construct's Q^2 value for an endogenous latent construct is larger than zero, its explanatory latent constructs exhibit predictive relevance (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). The results presented in Table 44 were produced through the Smart-PLS blindfolding procedure specified with no missing values, omissions distance 7 (103/7 does not equal an integer), and all constructs selected. The cross-validated redundancy measure is reported as it is the measure that best fits the PLS-SEM approach (Hair, Ringle, and Sarstedt 2011). All values are greater than zero indicating that explanatory constructs exhibit predictive relevance.

Table 44. Cross-Validated Redundancy

	1-SSE/SSO (Q^2)
Q4_Acquisition	0.617
Q5_SharedInfo	0.249
Q3_Heterogeneity	0.591
Q7_Incentives	0.366
Q6_Interpretation	0.276

PLS-SEM analysis is based on the assumption that all observations come from a single population. In many real world applications, however, this assumption of respondent homogeneity is unrealistic, as different population parameters are likely to occur for different subpopulations. Segment heterogeneity poses a threat to the validity of PLS-SEM results, so researchers should test potential sources of this type of heterogeneity (note this population heterogeneity is separate from the construct Knowledge Heterogeneity). Finite mixture partial least squares (FIMIX-PLS) is regarded as the primary approach for evaluating PLS path modeling results (Sarstedt and Ringle 2010). Using this technique, researchers can assess whether their results are distorted by unobserved heterogeneity (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). The FIMIX-PLS Algorithm in Smart-PLS was specified with the default settings of no missing values, three segments, stop criterion of 1.0E-4, and maximum iterations of 200. The resulting EN value equals 0.87; values greater than 0.50 indicate heterogeneous segments do exist in the data. Upon inspection of the results, however, two of three segments indicated are only 10 and 12 cases in size. This makes them relatively unimportant for interpretation for marketing purposes (Sarstedt and Ringle 2010).

Standardized path coefficients are used to assess the structural model relationships and quality. Individual path coefficients can be interpreted similar to standardized coefficients of ordinary least squares regressions. The significance of the path coefficients should be assessed using a resampling procedure such as bootstrapping. Paths that are significant and showing the correct sign empirically support hypothesized relationships and those that are not significant or display the wrong sign do not (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012). The bootstrapping procedure built into Smart-PLS was used to estimate inner model significance statistics for the path coefficients. The results presented in Table 45 were produced through a bootstrapping procedure specified with no missing values, 5000 samples, and 103 cases. Standard practice in PLS is to run at least 5000 samples using the same number of cases as the study sample (Hair, Ringle, and Sarstedt 2011; Hair et al. 2012).

Table 45. Path Coefficient T-Statistics

	Hypothesis	T-Statistic	
Q4_Acquisition	H2	2.149	**
Q6_Interpretation	H3	1.261	
Q5_SharedInfo	H4	0.456	
Q3_Heterogeneity	H5	1.514	*
Q7_Incentives	H7	1.287	

Single tailed t-tests tests at 95%** and 90%* confidence levels

Based on these scale operationalizations, the null hypothesis should be rejected for H2 (Acquisition) and H5 (Heterogeneity) which supports their role as significant drivers of forecast accuracy in the electronic prediction market run in this study. Conversely, the null hypothesis should fail to be rejected for H3 (Interpretation), H4 (SharedInfo), and H7 (Incentives) based on a confidence level of 90% which is appropriate for the purposes of an exploratory examination of drivers in new product forecasting, especially with a smaller sample (Gartner and Thomas 1993). Hypothesis H6 (Independence) was not tested as it was removed during scale purification.

Examining the path coefficients on Table 46 indicates that higher levels of new information acquisition and heterogeneity both lead to improved accuracy (as decreased APE) in a prediction market. Examining Table 47, the correlations are consistent with this conclusion.

Table 46. Standardized Path Coefficients

	Path Coefficients
Q4_Acquisition	-0.238
Q5_SharedInfo	-0.082
Q3_Heterogeneity	-0.164
Q7_Incentives	0.180
Q6_Interpretation	0.241

Table 47. Latent Construct Correlations

	APE	Q4_Acq	Q5_ShI	Q3_Het	Q7_Inc	Q6_Int
APE	1.000					
Q4_Acquisition	-0.129	1.000				
Q5_SharedInfo	-0.062	0.196	1.000			
Q3_Heterogeneity	-0.102	0.064	0.003	1.000		
Q7_Incentives	0.137	0.238	0.075	0.058	1.000	
Q6_Interpretation	0.108	0.384	0.222	0.280	0.122	1.000

Study II Discussion

The R-Square value of 0.103 is considered a low amount of explained variance by the model factors. The low R-Square value can be partially explained by strains on internal validity due to heavy influence of extraneous variables related to a field test (Churchill and Iacobucci 2005) and to a significant number of factors that influence the accuracy of market demand forecasts (Gartner and Thomas 1993). The forecast accuracy outcome is influenced by internal company and external marketplace factors outside of the model. In their analysis of new product forecasting, Gartner and Thomas identify 30 factors that influence new product forecasting accuracy including decision maker expertise and motivation, marketing research budgets, data sources and methods, marketing program factors, environmental factors, and competitive/industry factors. Kahn (2002) finds that when there are nonsignificant variables in a forecasting model (as occurs here) it indicates there are many drivers of forecast accuracy. It could be argued, however, that being able to explain even 10% of the variation in forecasting outcomes could have a significant impact on marketing decisions and financial outcomes in marketing (Kahn 2002).

This research established that forecast accuracy in a prediction market is driven most by i) new information acquisition, participants searching for and obtaining additional or different information to use in their individual predictions and ii) knowledge heterogeneity, participants having different perspectives, information, experiences, skills, and abilities to bring to a prediction as a result of being different from each other. These findings correspond with theory presented in the supporting literatures. For example, March (1991) finds that learning heterogeneity and new information brought in to the organization are two of the most important factors in organizational learning. New information acquisition is a dominant factor in the market based knowledge theory as it pertains to new product development, capabilities, and decision making literatures. This also supports the consistent finding in the prediction markets' literature of the importance of diversity to market accuracy.

In this analysis, nonsignificant results were found for the factors using shared information, incremental incentive, and different interpretations. The lack of significance may be due to a few issues. An internal validity issue may be due to noise from unaccounted factors in the environment masking the relationships between variables (Cook and Campbell 1979). It may be due to the skewed data from censored variables inflating bootstrap standard errors and reducing statistical power. This is common given PLS-SEM's tendency to underestimate inner model relationships (Hair et al. 2012). Calantone and Di Benedetto (1988) also experienced lack of significance in their analysis of the new product development process due to a lack of variance. Lack of significance may not be due factors having no effect, it may likely be due to a small sample size; further analysis with a larger sample may show other factors to also be significant. Larger sample sizes, however, may not be easy to obtain in a company field test of a prediction market. The sample frame of a post survey is restricted by the number of people who participated in a market. A 200-300 participant prediction market would be considered a large market, and even with a 60% response rate, the sample size would be 120-180. Even though some factors were not significant in this test, they should be retained because they increase the predictive strength of the model (Diamantopoulos and Siguaw 2000). It is important to note that use of shared information's lack of significance in this particular analysis should not lead to the conclusion that it is not a factor without an effect on forecast accuracy. Simply comparing the magnitude of differences in accuracy between some prediction market and internal forecasts (e.g. SBU# New Product Trial) suggests that these internal forecasts may have lacked independence.

Although not significant, it is still interesting to consider that the incremental (extrinsic) incentive and different interpretations factors exhibited a positive relationship with forecast error, the opposite to the hypothesized effect. Examining these two effects further could lead to some important understanding of how prediction markets work and how best to implement and manage them. The incremental incentive effect could suggest that participants that are driven by winning cash or prizes, have the wrong motivation and do not follow a process that leads to more accurate predictions but to playing a game to win a prize. This could suggest that the prize dimension should not be over developed and communicated in setting up prediction markets so to not attract or motivate counter-productive behavior. Incentives should be limited to gaining attention and interest only. The opposite different interpretations effect could suggest that actually calculating the forecasts is a standard process that is best improved by bringing more and better information to the task rather than employing novel or unconventional methods. This reinforces the importance of the significant factors of new information acquisition and knowledge heterogeneity.

In addition to the direct effects model analyzed here, a moderator analysis was completed within PLS for possible interactions between several theoretically supportable combinations of constructs. As shown on Table 48, no significant interactions were found which supports the model presented and further clarifies the definitions of the constructs themselves.

Table 48. PLS-SEM Structural Model Moderator Check

	Coefficient	T Statistic
Acquisition * Heterogeneity >> APE	0.134	0.692
Acquisition * Interpretation >> APE	0.225	1.151
Acquisition * Incentive >> APE	-0.173	0.957

CHAPTER 6

DISCUSSION

This dissertation introduces prediction markets as potential tool to improve marketing forecasting outcomes and support decision making in new product development and other important areas. Before the value of their adoption can be recommended, two research questions must be answered: do prediction markets produce better marketing forecasts than methods traditionally employed by firms, and if they do, how do they do it? Elements from the literatures for market knowledge, collective intelligence, and prediction market designs contributed to a theoretical and path model proposed to explain how prediction markets achieve improved forecast accuracy. The adapted market knowledge elements include new information acquisition, differences in interpretation, and use of shared information. The collective intelligence elements include knowledge heterogeneity, forecast independence, incremental incentive, and information aggregation.

Research Overview

Two field studies are implemented to answer the research questions. The first is an empirical test of prediction markets compared to traditional forecasting methods implemented within a Fortune 100 firm. The second, based on a post survey, is an analysis of how the combined prediction market design factors produce superior results. Study I compares prediction market forecasts against internal company forecasts for 17 actual business questions, across three different business units, in the areas of new products, supply chain, and overall business unit sales. Using accuracy measures established in the forecasting literature, Study I finds that prediction markets provide superior results in 67% of the forecasts, reduce average error by approximately 19%, and reduce the error range by over 40%. Therefore, for nearly two thirds of the time, the prediction market provided forecasts that are an improvement over the existing internal forecast. These results answer the first research question and support hypothesis one. Study I also finds that combining the prediction market and the internal company forecasts reduces the relative negative performance of the prediction market forecast in each case were it was not better than the comparable internal forecast. The instances where the EPM predictions performed the best were cases for which there is limited information and knowledge to support the prediction or forecast (e.g. new products). This advantage is rooted in the markets' ability to generate new and different information for a prediction task.

Study II examines the effects of the combined market knowledge, collective intelligence, and prediction market designs factors on forecast accuracy. A measurement model is designed using multi-item scales with 29 indicators to measure the six factors as latent constructs. All scales meet validity and reliability requirements for an adequate measurement model except for the construct forecast independence and one indicator which are both deleted. PLS-SEM analysis is used to estimate and asses a structural model relating the five remaining constructs to forecast accuracy measured as absolute percentage error (APE). The analysis finds that that two factors, new information acquisition and knowledge heterogeneity, are the significant drivers behind prediction markets' superior accuracy. They exhibit path coefficients of 0.24 and 0.16 respectively in a model that explains 10.3% of the variation in forecast error. Although this is a low R-Square value, empirical tests of marketing forecasts as outcomes are influenced by many extraneous factors regarding the company and the competitive marketplace. Significance of the other factors may be hidden by error related to the small sample size of 103. Larger samples may reveal another significant factor; use of shared information for example. Given the scale of businesses examined and the potential financial impact of forecast errors, even small amounts of explained variance can be of great value to a firm. Two additional findings are of interest, incremental incentive and differences in interpretation may have negative relationships with forecast accuracy. Although not significant, both of their coefficients displayed effects in the wrong direction. These findings may have two implications. One implication is that participants driven by winning cash or prizes, may have the wrong motivation, and may be merely playing a game to win. This could mean that the prize dimension should not be over developed and should be limited to gaining attention and interest only. A second implication is that calculating forecasts is a standard process that is best improved by bringing more and better information to the task rather than participants employing novel or unconventional individual methods. This reinforces the importance of the significant factors of new information acquisition and knowledge heterogeneity.

Contributions

Prediction markets have been shown to combine the market knowledge factor of new information acquisition and the collective intelligence factor of knowledge heterogeneity to provide improved accuracy for marketing forecasts. The combination of these market knowledge and collective intelligence factors suggests prediction markets can be employed as a tool to develop and apply a form of task specific "collective market intelligence" to marketing forecasts and decisions. Collective market intelligence can be defined broadly as technology platforms that centrally combine the collective information and judgment of many different people across the firm to predict uncertain market outcomes related to specific marketing questions, tasks, and decisions. The rationale is if many diverse people are able and willing to share new information and different opinions, and their opinions are aggregated, then the quality of market knowledge and decisions may be improved.

Results from the field studies make several contributions to marketing theory. First, this research makes a contribution to theory regarding prediction markets demonstrating their value as an alternative method to improve forecasting within firms (Armstrong 2006; Van Bruggen et al. 2010; Spann and Skiera 2003; Gruca, Berg, and Cipriano 2003). This research responds to the calls in marketing and forecasting literatures to test and validate new forecasting methodologies by introducing prediction markets, a new methodology that can improve marketing forecasting and decision making outcomes (Wind and Mahajan 1997; Armstrong 2006). Armstrong (2006) observes that most comparative testing of prediction markets has been done in other domains and there has been little research into understanding prediction markets. This research responds to Armstrong's specific call for tests of prediction markets against other structured group methods and for research into how they improve accuracy, under what conditions, how they are best employed. Similarly it responds to Spann and

Skiera’s (2003) call for further field research in more realistic business forecasting settings, with alternative market designs, and into the impact of design factors. Prediction markets contribute to the call recently made in the MSI 2012-2014 Research Priorities for methods to be imported from other disciplines to help solve many of the problems of the big data era and to develop, better, real-time, intelligent systems and decision support systems. This is consistent with the MSI 2010-2012 Research Priorities requesting conceptual frameworks from other disciplines that enhance traditional methods of evaluating customer responses to marketing actions and guide decision making. Prediction markets may also serve as a form of information grafting suggested by Huber (1991): a faster way of acquiring and grafting on new members who possess knowledge not previously available within the organization.

Second, there are contributions to forecasting literature. In their research of firms, Mahajan and Wind (1992) find that, even though concept testing and pre-market volume forecasting were considered the two most important activities in new product development, they were performed most infrequently. This research responds to their indication that new product development processes need more formal and quantitative approaches, including better forecasting models in support of activities including concept screening and business analysis. There are calls in the marketing literature for marketing to improve its analytical metrics, methods, and skills in general to better understand the financial consequences of marketing actions (Rao and Bharadwaj 2008; Verhoef and Leeflang 2009). Prediction markets can help marketing forecasting be more analytical and quantitative in this way. The introduction of prediction markets responds to the request that marketing improve analysis, forecasting, and decision making by taking advantage of innovative and emerging techniques put forth in the forecasting literature and disciplines outside of marketing (Armstrong 2006; MSI 2010; MSI 2014; Mahajan and Wind 1988). This research reacts to Gartner and Thomas's (1993) suggestion that future studies focus on the broader view of factors that might help explain new product forecasting especially how different types and levels of expertise affect forecast accuracy? This understanding of prediction markets contributes to theory regarding the methods and benefits of combing forecasts in terms of a new way of combining forecasts Makridakis (1983); making combining easy and efficient (Clemen 1989); combining different data and methods (Armstrong 2001b); and combining forecasts for truly innovative products (Mahajan and Wind 1988). Finally, it responds to the need to determine ways to reflect uncertainty along with marketing forecast point estimates (Rao and Bharadwaj 2008).

Third, this research contributes to the new products literature in terms of how to improve the new product development process. Prediction markets contribute to new and improved ways to create, integrate, and use knowledge for new product initiatives (Marsh and Stock 2006; Leonard-Barton 1992). They address the common question of what mechanisms exist to support market knowledge competence within organizations (Li and Calantone 1998; March 1991). Prediction markets respond to the calls for tools and processes to screen, evaluate, prioritize, and decide on new concepts early, quickly, and frequently in the new product development process (Day 2011; Henard and Szymanski 2001; Eisenhardt and Martin 2000; Kahn 2002) This new knowledge will also respond to requests for ways to handle the uncertainties and challenges faced during the launch phase of the new product process (Di Benedetto (1999); Kahn 2002). This research introduces a methodology to support information development and sharing when insights, experience, and capabilities are limited. This may be useful, for example, in cases where new products exhibit high degrees of innovativeness (Anderson and Ortinau 1988).

Fourth, prediction markets respond to many calls and requests for research into what new tools can enhance knowledge creation and application and support decision making (Eisenhardt and Martin 2000). For example, this research responds to Day's (2011) call for new tools and approaches to make marketing decision processes faster, more flexible, collaborative, better at sharing information, and able to work with less than perfect information. Specifically, prediction markets are uniquely suited to support the just-in-time decision making he says are demanded by today's marketplace. Prediction markets satisfy what Wind and Mahajan's (1997) indication that new approaches should be developed that leverage the power of information technology to quickly assess new product concepts within a few days rather than months. Also their identified the need for new processes to utilize marketing research as part of decision support systems, decision tools, and decision-making processes…including forecasting for new products and services. These findings respond to Krishnan and Ulrich's (2001) call for more research into the benefits of new tools to manage product knowledge and support decision making and how they can be expanded within the new product development process. This research contributes to Wierenga, Van Bruggen, and Staelin's (1999) need for study into knowledge-based systems that do not rely on quantitative modeling of data and that can incorporate the judgments of managers. They also find there is a need to examine decision support systems in real-life marketing situations, especially controlled experiments comparing outcomes from decision support systems to outcomes that would have occurred without them.

Fifth, this study contributes to the organizational learning literature in terms of the creation and use of market knowledge. This research introduces prediction markets in response to calls for research into new tools to support aspects of market information processing to improve marketing decision making (Sinkula, Baker, and Noordewier 1997). MSI 2010-2012 research priorities call for research into how firms can integrate and interpret market information to provide decision relevant information and improve marketers' decision making capabilities. This research explains how prediction markets can be a new form of task-specific, individual level market information processing that can overcome organizational impediments to learning and decision making and tap into information resources dispersed across the firm (Sinkula 1994; Huber 1991). This is an improvement over market intelligence that is dispersed throughout an organization, in the minds and practice of individuals and groups that needs to be accessed then applied to a particular marketing task. This work addresses Huber's (1991) call to investigate intra-organizational information distribution: how information held within an organization gets to those who need it. It responds to Day's (2011) more recent indication that research is needed on overcoming organizational impediments to extracting marketing insights from the organization and taking advantage of past experiences in order to improve marketing capabilities. As a collection of individual opinions, prediction markets are a new form of shared interpretation that does not require group consensus or executive decision to be used. This contributes to Sinkula's (1994) call for new constructs and models of market information processing as shared cognitions. The collective also offers a way to integrate and directly link, at the task level, the analysis of individual and organizational levels of market-based organizational learning which responds to calls for empirical research into information interpretation as an organizational process rather than an individual process (Huber 1991; Slater and Narver 1995). In terms of level of analysis, this research contributes to Moorman (1995) and Huber's (1991) questions about how organizational and individual levels of information processing are related, how individual level processing becomes organizational, and whether there are other intermediate levels that may be useful. This research also contributes the understanding the interplay between behavioral and cultural dimensions of the creation and use of market knowledge and its use in decision making (Kirca, Jayachandran, and Bearden 2005; Kahn et al. 2012; Moorman 1995).

Results from the field studies also make contributions to marketing practice. Prediction markets provide a new technology and tool to directly support marketing decision making. They are a new, faster, and better way to help marketers interpret data, forecast demand, make better decisions, and manage new products (MSI 2010-2012; MSI 2012-2014; Wind and Mahajan 1997; Armstrong 2006; Day 2011; Thomas 1987). Wierenga, Van Bruggen, and Staelin (1999) identify a need for tools designed for situations with low structured problems, in dynamic markets, with limited available data which applies to many, if not most, situations in practice. Day (2011) calls for intelligent application of technology tools with new analytical, collaborative and knowledge sharing capabilities. He notes specifically the need for "advances in internal (social) networks that enable cross-company, regional, and functional sharing of the organization's market knowledge" (p.189). Specifically, the application of prediction markets described in this dissertation responds to calls by researchers to introduce innovative methods into the forecasting process. MSI 2010-2012 research priorities recommend looking for conceptual frameworks and tools from other disciplines that may enhance traditional methods.

For specific tasks and projects, prediction markets can help managers tap into resources dispersed throughout the firm, across different functions or operating divisions and with network partners such as agencies, suppliers, and even customers. They can collect and combine various information and knowledge in a way that it can be applied to decisions; one of the biggest challenges in marketing (Slater and Narver 1995; Day 2011; Huber 1991). Prediction markets not only collect and combine information, but they also collect and combine various experiences, perspectives, insights, skills, and expertise existing in people throughout the expanded firm. They also support effective forecasting and decision making by helping overcome impediments to learning and decision making such as organizational biases and filters and shared assumptions and beliefs.

With the functionality described for prediction markets, project managers are supported in their evaluation and selection of new concepts in the early phases of the new product development process. This responds to calls to provide marketing practitioners with a new and effective tool to prioritize diverse innovation opportunities and forecast their market potential at very early stages (MSI 2010-2012; Henard and Szymanski 2001). Equally as important, this functionality can support market demand forecasting in the later launch phases of the new product development process, supporting manufacturing, inventory, distribution, and promotional planning.

More accurate demand forecasts can significantly aid in developing and sending the best products to market and supporting effective and efficient distribution and promotion of these products. This greatly improves the odds of new product and marketing success, fuels growth for the firm, and ultimately provides competitive advantage (Rao and Bharadwaj 2008).

Limitations and Future Research

The research of this dissertation has a few limitations that should be considered. The first limitation is the prediction market was implemented only as an internal market which means no parties outside of the company were invited to participate. As a result, the market did not benefit from the knowledge, experience, or expertise of their agencies, partners, customers, or any other network members. Based on the importance of new information and knowledge heterogeneity to improving forecast accuracy, this is a serious shortcoming for optimal performance. Future research studies should attempt to open up markets to external participants and practical applications should incorporate this as an important design dimension to maximize accuracy improvements.

The second limitation is the smaller sample size of 103 respondents in the post survey. Although this sample was sufficient for PLS-SEM analysis, at least one factor (use of share information) might have been found significant with even a slightly larger sample. Lack of significance may not be due lack of effect in this case, but to the survey's small sample size that was shaped by the prediction market design. A larger sample size, however, may not be easy to obtain in a field test. The sample frame of a post survey is restricted by the number of people who participate in the prediction market. A 200-300 participant market would be considered a large market, and even with a 60% response rate the sample size would still only be 120-180 respondents.

The third limitation may be the lack of significance of the forecast independence construct; likely due to lack of variance in the measures. Examining the distributions of the indicators for this factor show that most participants felt they had independence while participating in the market. Given the research design of this study, they were all in fact benefiting from the anonymity and independence offered by the market; the control condition essentially did not exist for this manipulation. Future research should reconsider how best to manipulate this factor.

The fourth limitation is the absence of a formal manipulation and test of the effect of the aggregation mechanism of the market. Information aggregation in this analysis was treated as an enabling or instrumental factor. It was considered as a binary condition; it was present and the prediction market existed and functioned and other effects were possible or it was not present. Future research should attempt to manipulate and test this factor.

There are at least a few opportunities to extend this analysis of prediction markets and their outcomes. First, prediction markets can be applied to areas beyond new products where marketing must make predictions and decisions about uncertain market outcomes. This could include supporting decisions about other dimensions of the marketing mix, such as entering new markets and channels, developing new merchandising and promotional programs, and investigating changes to pricing structures. Prediction markets could also be used to assess trends and changes in other marketplace and environmental factors that serve as inputs to marketing decisions. These could include macroeconomic, material cost, or consumer category consumption trends. Second, in order to control for extraneous influences and focus on testing the effects of the focal constructs, an interesting feature of prediction markets was disabled. Participants were not allowed to interact with each other through a forum or share other information, rationales, or perspectives. This dynamic could not only influence the improvement of accuracy over time, but it would also leave a data trace in the system. Future studies should allow for feedback from and interaction between participants and analyze this communication data against the change in predictions, their central values and distributions, and their error. Third, there is an opportunity to analyze how predictions, their central values and distributions, and their error change over time and how this affects accuracy over time. This may lead to an understanding of the diminishing returns of market durations, the optimal amount of time markets should remain open, and factors that affect this optimal duration. Fourth, the effect of allowing the internal forecast teams to read data from the open market over time and respond with adjustments to their original forecasts in real time rather than waiting until the market closes and doing a post diagnosis. This may add a new dimension to and accelerate the value of prediction markets and combining forecasts.

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APPENDIX A

EPM RECRUITING COMMUNICATIONS

From: SBU Research Director
To:
Date: 08/11/2011

Subject: Announcing The EMP Challenge--Your Opportunity to Participate!

Colleagues:

We have the unique opportunity to for a little healthy competition and participate in a pilot program using Electronic Prediction Markets (EPM) to help us refine our current business forecasts.

This pilot – called the EPM Challenge – gives us access to an innovative research tool customized with questions about the changing conditions and key issues facing [SBU]. Everyone is able to participate in creating a forecast – and we'll add some fun to the process by giving awards for the most accurate forecasting in our division, as well as some randomly drawn awards based on participation.

The Challenge starts today, so to get started:
Use this link - https://clients2.lumenogic.com/cpb/login/register.html - to register and access the EPM tool. Be sure to bookmark this link so you can return to the tool to update your input through the end of the EPM Challenge on September 22.

What is an EPM?
EPMs are competitive forecasting markets created for the purpose of building on the shared knowledge of participants and consolidating their informed opinions. The system of using prediction markets is based on the developing field of collective intelligence as described in the book The Wisdom of Crowds by James Suroweicki.

Any questions you may have about the EPM Challenge should be sent to me.

I encourage everyone to participate. Thank you for your enthusiasm and commitment.

Best Regards,

From: SBU Research Director
To:
Date: 08/19/2011

Subject: Don't forget the Electronic Prediction Market Challenge!

Dear Colleagues:

I would like to remind you that [Company’s] Electronic Prediction Market is open for you to showcase your forecasting skills and assist us in this leading-edge experiment. We've gotten a great deal of positive feedback on how interesting the site is and how easy to use it is. In the past few days, over 90 people across [Company] North America have entered their predictions, but we need more participation! If you have already made your forecasts, I would like to thank you and remind you that you can modify your forecasts at any time.

As mentioned, there will be rewards and recognition for the most accurate and timely forecasts as well as random prizes awarded for participation. You earn more points toward the rewards for earlier and more precise forecasts.

So if you have not yet participated, *NOW IS THE TIME!!* Are you up to the challenge?

https://clients2.lumenogic.com/cpb/login/register.html - to register and access

Thanks,

From: SBU Research Director
To:
Date: 08/29/2011

Subject: Electronic Prediction Market--A Reminder

Fellow [SBU] Colleagues--

The Electronic Prediction Market is still open but our participation rate versus SBU1and SBU3 is lagging!

	Invited	Registered	%
SBU1	103	45	44%
SBU2	120	28	23%
SBU3	305	46	15%

For those that have signed up and entered forecasts, thank you for providing valuable information that we will help us develop more accurate and earlier forecasts for important business issues we face. It also means that you're are all eligible for the valuable prizes that will be given out to the most accurate forecasters!
Feel free to go back into the market and update your forecast. You can see the distribution of other forecasts and how your estimate compares, and make adjustments to your own.
For those who haven't yet signed up, here's the link to register and access:
https://clients2.lumenogic.com/cpb/login/register.html
Keep up the good work!

From: SBU Research Director
To:
Date: 09/15/2011

Subject: Don't miss your chance to win $250 in the Electronic Prediction Market

---

That's right...the SBU member who makes the most accurate predictions in the Electronic Prediction Market will win a $250 Amazon gift cart. Second place will receive a $150 gift card. Just for participating, you could have a shot at one of five $50 gift cards.

It's not too late, the market remains open until Oct 2. Log on and make your initial predictions, and then go back and see how your predictions compare to what everyone else is saying. You can update and change your predictions as many times as you like until Oct 2 to improve your accuracy.

As a matter of pride, SBU2 is getting smoked by SBU1 and SBU3 in terms of our participation rate:

	Participation %
SBU1	46%
SBU2	23%
SBU3	18%

Here's the link to register and access:
https://clients2.lumenogic.com/cpb/login/register.html

Thanks for your participation!

From: SBU Research Director
To:
Date: 09/23/2011

Subject: Final Two Weeks for your chance to win $250 in the Electronic Prediction Market

---

Time is running out...the Electronic Prediction Market Challenge is only open for another two weeks. The positive feedback has been overwhelming from those who have participated thus far. Don't miss your chance to win a $250 or a $150 Amazon gift card or a shot at one of five $50 gift cards.

It's not too late, the market remains open until Oct 2. Log on and make your initial predictions, and then go back and see how your predictions compare to what everyone else is saying. You can update and change your predictions as many times as you like until Oct 2 to improve your accuracy.

As a division, our participation rate has improved in the last week, but SBU2 is still getting smoked by SBU1 and SBU3! There's still time to close the gap and get in on your chance to win one of seven prizes!!

Here's the link to register and access:
https://clients2.lumenogic.com/cpb/login/register.html

Thanks for your participation!!!

From: VP Research
To:
Date: 09/27/2011

Subject: Last chance to participate in [Company's] Electronic Prediction Market – Market Closes on Sunday 10/2

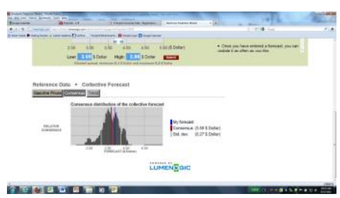
Dear Prediction Market Team Member,

This is the last chance for you to cast your votes in our [Company's] Electronic Prediction Market (EPM) pilot. This innovative tool, which has been designed tap into the *Wisdom of [Company's] Crowd* will be closing this Sunday (October 2).

THANK YOU to the 180 people who have joined the prediction market so far!

To those who have yet to participate, I will encourage you to do so today, as only a limited number of people were invited to the EPM. As a member of [Company's] Prediction Market team, you are part of an important effort to support innovation and planning at [Company]. You were selected for your unique knowledge and perspective on our business. Let us know what you think!

Our EPM is an on-line forecasting competition that is collecting and combining hundreds of your votes to answer real [Company's] business questions. Over 1,100 forecasts have already been entered. For example, we are currently forecasting the price of gas (an important cost factor) to be $3.59 in November.



There are other open questions to vote on including: new product concepts, recently launched products, sales, and shipments.

As mentioned, there will be rewards and recognition for the most accurate and timely forecasts as well as random prizes awarded for participation. Don't miss your last chance to contribute and win - there's a prize pool of $2,000.

If you haven't participated, please register now at https://clients2.lumenogic.com/cpb/login/login.html. It takes no more than 10 minutes and you can do it 24/7 from work or home. If you have already participated, check back to see the collective forecasts and trends; updating your forecasts could help you win.

Thank you for participating and good luck!

From: SBU Research Director
To:
Date: 09/30/2011

Subject: Final Two Weeks for your chance to win $250 in the Electronic Prediction Market

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IF you haven't entered the Electronic Prediction Market challenge for your chance to win a $250, $150 or one of five $50 Amazon gift cards, you're almost out of time! The market will close this Sunday, Oct 2, so don't delay any longer!

For the last time, here's the link to access the market and register if you've haven't already done so: https://clients2.lumenogic.com/cpb/login/register.html

We obviously have to wait for real-world results for the second quarter to come in to declare our winners, but we'll be in touch.

Thanks to all who have participated in this ground-breaking experiment.

Regards,

APPENDIX B

POST SURVEY RECRUITING COMMUNICATIONS

From: Research VP
To:
Date: 10/13/2011

Subject: [Company's] Electronic Prediction Market Post Survey Announcement.

Dear Prediction Market Team Member,

Many thanks for recently participating in [Company's] Electronic Prediction Market (EPM) pilot!
We greatly appreciate your involvement with this initiative and look forward to working with the market results. EPM prizes for accuracy and participation will be awarded after we have actual sales results at the close of our Q2.

To maximize our learning about prediction markets, our research partners from Temple University have put together a brief, online follow up survey.

To show their appreciation for your time and effort, the Temple University research team will have a random drawing of THREE iPad2s amongst the 200 people who complete the survey.
16GB Apple® iPad2s with Wi-Fi feature

Your input on this survey is extremely important. Your responses will help us understand the factors that make prediction markets successful. Moreover, your participation will assist Mark Lang, a doctoral student at Temple University, in completing his dissertation and earning his Ph.D..

Only a limited number of people were invited to participate in the EPM based on their unique knowledge and perspective. It is therefore very important that you complete this survey in order to achieve a sufficient sample size.

The instructions are easy to follow, and based upon pretests, Mark has found it takes only several minutes to complete. Simply copy this link into your browser to get started:
https://clients2.lumenogic.com/cpb/public/survey.html

The survey will be open from 10/12 through 10/31. Drawings for the iPad2s will occur during this period, so I encourage you to complete the survey now to contribute to the research and be eligible to win one of the prizes.

If you have any questions about the survey, please contact Mark Lang directly:
610-660-3431 or mark.lang@temple.edu.

Thank you again for taking time out of your busy schedule to contribute to [Company's] EPM pilot!

From: Research VP
To:
Date: 10/20/2011

Subject: [Company's] EPM Survey Reminder: First iPad2 Drawing on Sunday.

This is a friendly reminder that [Company's] EPM Post Survey will be closing soon on Monday October 31st.

Thank you to those who have completed the survey so far, but we still need a good turnout from all who were invited so that we will be able to complete our analysis.

Don't forget, your completed survey contributes to an innovative [Company] research project, a Ph.D. dissertation, and earns a chance to win one of THREE iPad2s!

The drawing for the first ipad2 will be this Sunday, so I encourage you to complete the survey now to be eligible to win this prize.

Simply copy this link into your browser to get started:
https://clients2.lumenogic.com/cpb/public/survey.html

If you have any questions about the survey, please contact Mark Lang directly at 610-660-3431 or mark.lang@temple.edu.

Thank you for contribution to [Company's] EPM pilot!

-------- FORWARD MESSAGE --------

Previous announcement

From: Research VP
To:
Date: 10/28/2011

Subject: [Company's] EPM Survey Reminder: Second iPad2 Drawing on Friday.

[Employee name] is the winner of our first iPad2 Drawing! There are still two more iPad2s to be drawn.

This is the final reminder that [Company's] EPM Post Survey will be closing on Monday October 31st.

Thank you to those who have completed the survey so far, but we still need a good turnout from all who were invited so that we will be able to complete our analysis.

Don't forget, your completed survey contributes to an innovative [Company] research project, a Ph.D. dissertation, and a chance to win one of TWO remaining iPad2s!

The second iPad2 drawing will be this Friday, so I encourage you to complete the survey now to be eligible to win this prize.

Simply copy this link into your browser to get started:
https://clients2.lumenogic.com/cpb/public/survey.html

If you have any questions about the survey, please contact Mark Lang directly at 610-660-3431 or mark.lang@temple.edu.

Thank you for contribution to [Company's] EPM pilot!

APPENDIX C

FINAL CONSTRUCT SCALES AND SCALE ITEMS

Var Name	Scales and Items	Sources
	New information acquisition defined as participants searching for and obtaining additional or different information to use in their individual predictions.	Moorman and Miner 1997 Bearden, Hardesty, and Rose 2001 Rindfleisch and Moorman 2001 Deshpande and Zaltman 1982 Pelled, Eisenhardt, and Xin 1999 Also based on Watson, Kumar, and Michaelsen 1993 Jackson, May, and Whitney 1995
Q4_1	Try to search for more information similar to the description?	
Q4_2	Try to search for different information than in the description?	
Q4_3	Eventually obtain more information similar to the description?	
Q4_4	Eventually obtain different information than in the description?	
Q4_5	Collect information from sources inside your business unit?	
Q4_6	Collect information from sources outside your business unit?	
Q4_7	Look for information about customers or competitors?	
Q4_8	Think that obtaining other information would provide you with an advantage?	
Q4_9	Know where to look to find needed information?	
Q4_10	Reexamine the value of information from previous studies?	
	Use of shared information defined as participants using the information shared in the system to make or update their predictions.	Kohli, Jaworski, and Kumar1993 Baker and Sinkula 1999 Slater and Narver 2000 Li and Calantone 1998 Hurley and Hult 1998 Tjosvold and Poon 1998 Mohammed and Ringseis 2001 Sethi 2000 Also based on Moorman 1995 Jackson, May, and Whitney 1995
Q5_1	Look at the supporting information shared with the original question?	
Q5_2	Look at the consensus prediction available in the system? (the displayed...)	
Q5_3	Find the shared supporting information adjusted your thinking?	
Q5_4	Find the consensus prediction in the system adjusted your thinking?	
Q5_5	Find the shared supporting information useful?	
Q5_6	Find the consensus prediction in the system useful?	
Q5_7	Reenter the EPM and Update your prediction as the market progressed?	

Var Name	Scales and Items	Sources
	Differences in interpretation defined as participants employing different information and thinking to make their individual accurate predictions.	Strutton and Lumpkin 1994 Moorman 1995 Deshpande and Zaltman 1982
Q6_1	Actually USE more information similar to that in the description?	Chaston, Badger, and Sadler-Smith 2000
Q6_2	Actually use different information than that in the description?	Day and Nedungadi 1994
Q6_3	Actually use a different perspective or knowledge than the people in the description?	Cheng, Luckett, and Schulz 2003
Q6_4	Follow a different approach, process, or analysis than that in the description?	Rindfleisch and Moorman 2001
Q6_5	Actually use different experience, skills, or abilities than the people in the description?	Moorman1990
Q6_6	Integrate information from different sources?	Also based on
Q6_7	Think that information enriched your basic understanding of this prediction task?	Jaworski, and MacInnis 1989
Q6_8	Analyze data to make this prediction?	Surowiecki 2005
Q6_9	Strive to be very accurate in this prediction?	Watson, Kumar, and Michaelsen 1993 Jackson, May, and Whitney 1995
	Knowledge heterogeneity defined as participants having different information and thinking to bring to a prediction as a result of being different from each other.	Moorman and Miner 1997 Bearden, Hardesty, and Rose 2001 Rindfleisch and Moorman 2001
Q3_1	HAVE access to different information than in the description?	Deshpande and Zaltman 1982
Q3_2	Have a different perspective than the people in the description? (e.g. viewpoint,...)	Pelled, Eisenhardt, and Xin 1999
Q3_3	Have different knowledge than the people in the description? (e.g. local, specialized)	Also based on
Q3_4	Have different experience than the people in the description?	Watson, Kumar, and Michaelsen 1993
Q3_5	Have different skills and abilities than the people in the description?	Jackson, May, and Whitney 1995
Q3_6	Have different tools and techniques than the people in the description?	
Q3_7	Think your work area has different resources than the people in the description?	

Var Name	Scales and Items	Sources
	Forecast independence defined as participants being willing and able to share information and opinions because they are free from organizational influence and can choose their own sources and approach.	Sparks 1994 Hartline and Ferrell 1996 Singelis 1994 Deshpande and Zaltman 1982 Chaston, Badger, and Sadler-Smith 2000 Van De Ven and Delbecq 1974 Tjosvold and Poon 1998 Also based on Hurley and Hult 1998 Sinkula, Baker, and Noordewier1997 Baker and Sinkula 1999 Abbey and Dickson 1983 Venkatesh, Kohli, and Zaltman 1995
Q8_1	Choose and use your own sources of information?	
Q8_2	Follow your own process or analysis?	
Q8_3	Act free from any consequences resulting from your prediction?	
Q8_4	Use your own judgment in solving the problem?	
Q8_5	Exercise independent thought and action?	
Q8_6	Make your own decisions?	
Q8_7	Act free from influence by your peers or organization?	
	Incremental incentives defined as extrinsic or intrinsic rewards that provide motivation for participants to invest time and effort into searching for information and making an accurate prediction.	Schmid 2002 Beer and Katz 2003 Ingram and Bellenger 1983 Also based on Chiang and Birtch 2005 Abbey and Dickson 1983
Q7_1	The chance to earn some extra cash?	
Q7_2	Potential recognition from your organization as a top performer?	
Q7_3	Participating in a novel exercise?	
Q7_4	Status among your peers as a top performer?	
Q7_5	Being part of an innovative methodology or experiment?	
Q7_6	The chance to win prizes in a competition?	
Q7_7	The chance to help the company improve business results?	
Q7_8	The spirit of competition in a contest with your colleagues?	
Q7_9	The challenge of solving a puzzle?	

APPENDIX D

PRE-ANALYSIS DATA SCREENING

Scale Item	N	Mean	Std. Dev.	Skew.	Std. Error Skew.	Kurtosis	Std. Error Kurtosis	Range
Q3_1	103	3.39	1.911	.364	.238	-1.068	.472	6
Q3_2	103	3.93	1.942	.065	.238	-1.104	.472	6
Q3_3	103	3.47	1.872	.237	.238	-.987	.472	6
Q3_4	103	4.14	2.058	-.097	.238	-1.317	.472	6
Q3_5	103	4.01	1.973	-.053	.238	-1.227	.472	6
Q3_6	103	3.89	1.852	.046	.238	-1.050	.472	6
Q3_7	103	3.78	1.935	.149	.238	-1.170	.472	6
Q4_1	103	2.55	1.607	.545	.238	-1.113	.472	5
Q4_2	103	2.51	1.697	.858	.238	-.347	.472	6
Q4_3	103	2.72	1.779	.501	.238	-1.107	.472	6
Q4_4	103	2.52	1.725	.688	.238	-.817	.472	6
Q4_5	103	2.90	1.892	.585	.238	-.853	.472	6
Q4_6	103	2.25	1.637	.978	.238	-.478	.472	5
Q4_7	103	2.41	1.774	1.112	.238	.162	.472	6
Q4_8	103	3.37	1.990	.182	.238	-1.209	.472	6
Q4_9	103	3.11	1.920	.515	.238	-.817	.472	6
Q4_10	103	2.40	1.586	.731	.238	-.658	.472	6
Q5_1	103	4.27	1.951	-.311	.238	-.995	.472	6
Q5_2	103	4.04	2.009	-.276	.238	-1.139	.472	6
Q5_3	103	3.55	1.713	-.087	.238	-1.209	.472	6
Q5_4	103	3.37	1.873	.205	.238	-1.156	.472	6
Q5_5	103	4.08	1.918	-.283	.238	-1.051	.472	6
Q5_6	103	4.03	1.958	-.369	.238	-1.119	.472	6
Q5_7	103	2.28	1.785	1.148	.238	.054	.472	6
Q6_1	103	3.00	1.826	.345	.238	-1.256	.472	6
Q6_2	103	2.93	1.784	.495	.238	-.974	.472	6
Q6_3	103	3.64	1.857	.082	.238	-1.045	.472	6
Q6_4	103	3.37	1.889	.306	.238	-.962	.472	6
Q6_5	103	3.66	1.763	.084	.238	-.983	.472	6
Q6_6	103	3.07	1.773	.455	.238	-.964	.472	6
Q6_7	103	3.66	1.813	-.143	.238	-1.058	.472	6
Q6_8	103	3.09	1.816	.319	.238	-1.112	.472	6
Q6_9	103	3.86	1.732	-.052	.238	-.754	.472	6

Scale Item	N	Mean	Std. Dev.	Skew.	Std. Error Skew.	Kurtosis	Std. Error Kurtosis	Range
Q7_1	103	4.86	1.889	-.494	.238	-.877	.472	6
Q7_2	103	3.68	2.092	.168	.238	-1.302	.472	6
Q7_3	103	5.11	1.697	-.637	.238	-.474	.472	6
Q7_4	103	3.32	1.921	.403	.238	-.934	.472	6
Q7_5	103	5.08	1.631	-.708	.238	-.062	.472	6
Q7_6	103	5.20	1.795	-.800	.238	-.383	.472	6
Q7_7	103	4.98	1.669	-.576	.238	-.500	.472	6
Q7_8	103	4.61	1.921	-.479	.238	-.927	.472	6
Q7_9	103	4.88	1.896	-.807	.238	-.426	.472	6
Q8_1	103	5.46	1.731	-.955	.238	-.318	.472	6
Q8_2	103	5.70	1.487	-1.016	.238	-.064	.472	5
Q8_3	103	6.11	1.342	-1.637	.238	1.922	.472	5
Q8_4	103	6.11	1.244	-1.546	.238	1.806	.472	5
Q8_5	103	6.09	1.253	-1.570	.238	2.059	.472	5
Q8_6	103	6.16	1.227	-1.830	.238	3.059	.472	5
Q8_7	103	5.91	1.476	-1.563	.238	1.986	.472	6

APPENDIX E

FACTOR ANALYSIS - ROTATED COMPONENT MATRIX

	Component								
Item	1	2	3	4	5	6	7	8	9
Q3_1	.070	.750	.074	.048	-.011	-.038	-.166	.222	-.025
Q3_2	.020	.831	.122	-.010	.212	.022	-.003	-.018	.088
Q3_3	.141	.826	-.023	.043	.115	-.007	-.071	-.087	.123
Q3_4	.069	.865	.189	.002	.143	-.073	-.005	-.086	-.055
Q3_5	-.085	.872	.130	-.004	.026	-.011	.059	-.028	-.032
Q3_6	-.019	.860	.044	-.077	-.106	.154	.064	.040	.024
Q3_7	-.082	.833	.087	-.004	-.062	-.019	.102	.051	-.008
Q4_1	.840	-.009	-.107	.193	.053	.172	-.033	-.005	-.080
Q4_2	.823	.037	.007	.114	.033	.183	-.029	-.092	-.038
Q4_3	.784	-.006	.010	.157	.235	.140	-.038	.018	.166
Q4_4	.834	-.017	.030	.043	.130	.169	-.021	.016	.154
Q4_5	.706	-.044	-.005	.234	.121	.192	-.205	.029	.174
Q4_6	.832	.095	-.088	.026	.084	.042	.115	.027	-.026
Q4_7	.831	.113	-.033	.038	.171	-.063	.104	-.062	-.035
Q4_8	.632	.193	-.023	.090	.095	.051	.033	.161	-.099
Q4_9	.658	-.161	.178	.021	.156	.020	.033	-.001	-.170
Q4_10	.765	.037	-.054	.077	.113	-.049	.203	.042	.026
Q5_1	.158	.001	.110	.702	.177	.192	.094	-.030	-.231
Q5_2	.128	-.031	-.016	.842	.035	-.065	.000	.163	.235
Q5_3	.215	.032	.043	.792	.078	.065	.044	.015	-.100
Q5_4	.358	-.027	.017	.733	.048	.014	-.102	.128	.289
Q5_5	.037	.000	.054	.842	.117	.106	.092	-.124	-.251
Q5_6	.140	.012	-.001	.866	.126	.011	.035	-.002	.069
Q5_7	.483	.253	-.209	.354	.056	.031	.189	.008	.447
Q6_1	.658	-.148	.023	.258	.390	-.012	-.200	.039	.123
Q6_2	.634	-.014	.055	.097	.600	-.031	-.022	.143	.127
Q6_3	.278	.153	.091	.132	.825	.114	.131	-.051	.093
Q6_4	.312	.226	.111	.190	.726	.113	.139	-.090	.022
Q6_5	.213	.192	.080	.097	.838	.059	.054	-.068	-.039
Q6_6	.573	-.131	-.032	.137	.606	-.030	.020	.101	-.087
Q6_7	.305	-.170	.093	.314	.529	.083	.091	-.068	-.516
Q6_8	.566	-.124	-.002	.239	.227	.304	-.113	-.099	-.301
Q6_9	.347	-.082	-.055	.063	.537	.305	.072	.160	-.190

	Component								
Item	1	2	3	4	5	6	7	8	9
Q7_1	.068	-.022	-.008	.091	-.018	.452	.020	.752	-.043
Q7_2	.122	.156	-.010	.035	.167	.772	.028	.285	-.084
Q7_3	-.056	.030	.348	.131	.096	.034	.819	-.015	-.116
Q7_4	.184	.069	.003	.043	.079	.801	.008	.214	-.098
Q7_5	.073	-.026	.195	.085	.137	.279	.848	.004	.027
Q7_6	.048	.078	.123	.014	-.026	.281	.099	.845	.064
Q7_7	.071	-.018	.168	-.047	.099	.407	.644	.220	.130
Q7_8	.117	-.068	.100	.046	.003	.772	.218	.061	.053
Q7_9	.135	-.099	.182	.158	.095	.692	.294	.015	.125
Q8_1	.152	-.041	.640	-.014	.277	.222	.103	-.215	.278
Q8_2	.084	.132	.742	-.018	.146	.163	.034	-.168	.266
Q8_3	-.142	.027	.808	.130	-.022	.020	.087	.122	-.212
Q8_4	-.037	.092	.897	.040	.038	.021	.086	.164	.020
Q8_5	-.049	.139	.907	.036	.036	.040	.111	.070	.061
Q8_6	-.032	.144	.911	.021	-.024	-.001	.080	.069	-.098
Q8_7	-.009	.135	.784	-.027	-.022	-.031	.148	-.062	-.168

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 7 iterations.

APPENDIX F

ITEM-LATENT CONSTRUCT LOADINGS

Scale/Indicator	Q4_Acq	Q5_ShI	Q3_Het	Q7_Inc	Q8_Ind	Q6_Int
Q3_2	0.086	-0.008	0.860	0.070	0.181	0.375
Q3_3	0.180	0.045	0.844	0.025	0.131	0.260
Q3_4	0.102	0.002	0.917	-0.026	0.099	0.300
Q3_5	-0.051	-0.004	0.894	0.036	0.088	0.220
Q3_6	0.005	-0.063	0.838	0.185	0.113	0.072
Q3_7	-0.071	0.042	0.801	0.082	0.131	0.069
Q4_1	0.890	0.227	0.004	0.255	0.091	0.277
Q4_2	0.883	0.170	0.061	0.200	0.053	0.287
Q4_3	0.860	0.231	0.053	0.204	0.168	0.392
Q4_4	0.869	0.122	0.030	0.247	0.268	0.365
Q4_6	0.850	0.123	0.091	0.200	0.099	0.298
Q4_7	0.807	0.113	0.115	0.078	0.134	0.428
Q5_2	0.212	0.811	-0.023	0.097	-0.054	0.139
Q5_3	0.302	0.505	0.039	0.151	0.010	0.240
Q5_4	0.417	0.603	-0.005	0.160	0.015	0.186
Q5_5	0.180	0.781	0.013	0.091	-0.087	0.240
Q5_6	0.265	0.970	0.020	0.100	0.000	0.258
Q6_3	0.420	0.268	0.248	0.169	0.048	0.831
Q6_4	0.460	0.252	0.295	0.167	0.129	0.828
Q6_5	0.347	0.201	0.267	0.103	0.235	0.992
Q6_6	0.615	0.258	-0.080	0.156	0.016	0.587
Q7_1	0.147	0.080	-0.050	0.829	0.000	0.021
Q7_2	0.245	0.077	0.140	0.847	0.015	0.209
Q7_4	0.273	0.067	0.055	0.842	0.068	0.179
Q7_6	0.090	0.018	0.067	0.739	0.098	-0.015
Q8_3	-0.170	0.071	0.103	0.102	-0.323	-0.002
Q8_4	-0.035	0.028	0.184	0.141	0.423	0.147
Q8_5	-0.038	0.031	0.234	0.118	0.448	0.162
Q8_6	-0.057	0.011	0.231	0.076	0.177	0.101

APPENDIX G

DISSERTATION FUNDING

I would like to thank the following organizations for the financial support they have provided that made this research and dissertation possible.

<table>
<tr><td>Temple University CIBER Grant</td><td align="right">$10,000</td><td rowspan="3">Technology Platform design and implementation by consultant-service provider.</td></tr>
<tr><td>Subject Company Grant</td><td align="right">$35,000</td></tr>
<tr><td>Lumenogic In Kind Services Grant</td><td align="right">$40,000</td></tr>
<tr><td>Saint Joseph’s University C.J. McNutt Chair Funding</td><td align="right">$3,450</td><td>Incentives to market participants and post survey respondents.</td></tr>
<tr><td align="right">Sub-Total</td><td align="right">$88,450</td><td></td></tr>
</table>

APPENDIX H

IRB INFORMED CONSENT FORM

Fox School of Business
TEMPLE UNIVERSITY®

Research Study: Collective Market Intelligence as an Adaptive Learning Capability

Principle Investigator: Neeraj Bharadwaj, PhD., Assistant Professor, Department of Marketing
Student Investigator: Mark Lang, PhD. Candidate, Department of Marketing

We are currently studying how Electronic Prediction Markets may improve forecasting outcomes. To gain insight into these questions, we are asking you to answer some questions based on your recent participation in the company's prediction market.

The information you provide will be recorded anonymously and your participation and survey responses will be held in the strictest confidence. Data will only be accessed and analyzed by the Temple investigators and will reside only at Temple University.

We welcome questions about the survey at any time. Your participation in this study is on voluntary basis, and you may refuse to participate at any time without consequence or prejudice.

For questions about your rights as a research respondent, you may contact the Institutional Review Board Coordinator at (215) 707-3390. The IRB Coordinator may also be reached by email: irb@temple.edu or regular mail:

Institutional Review Board Coordinator
Temple University Research Administration
Student Faculty Conference Center
3340 North Broad Street – Suite 304
Philadelphia, PA 19140

By clicking on this link and proceeding with the survey, you indicate that you have read and understand the contents of this Consent Form and that you agree to take part in this study.

__ Proceed with survey

Although the study team has placed safeguards to maintain the confidentiality of my personal information, there is always a potential risk of an unpermitted disclosure. To that degree, all documents and information pertaining to this research study will be kept confidential, unless required by applicable federal, state, and local laws and regulations to be disclosed. I understand the records and data generated by the study may be reviewed by Temple University and its agents, the study sponsor or the sponsor's agents (if applicable), and/or governmental agencies to assure proper conduct of the study and compliance with regulations. I understand that the results of this study may be published. If any data is published, I will not be identified by name.

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