Corporate Prediction Markets for Business Decisions: New Applications, Challenges and Limitations

Jessica A. Zinger

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Date: May 1, 2018
Corporate Prediction Markets for Business Decisions: New Applications, Challenges and Limitations

Jessica A. Zinger

A dissertation submitted in partial fulfillment of the requirements for the degree of
Ph.D. in Business
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Program Authorized to Offer Degree:
Management Department
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DEDICATION

To my girls, P & T, for helping keep all things in perspective.
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The road to a Ph.D. is truly different for everyone and I am blessed to have traveled this one with the acknowledged individuals. I could not have done this without them and I am truly grateful.
Abstract

Corporate Prediction Markets for Business Decisions: New Applications, Challenges and Limitations

Jessica A. Zinger

Chair of the Supervisory Committee:
Aaron Jackson
Professor of Economics

Prediction markets, introduced roughly 30 years ago, are a way to leverage market pricing for information aggregation. Research has shown the markets provide accurate (often superior) forecasts. To date, research has been predominately of an economic nature. Despite numerous articles on the application of prediction markets in businesses (Hewlett-Packard, Google) the management literature has largely ignored the topic. This dissertation follows a three-paper model to begin to address the perceived gap.

Paper one introduces a new application of the market, namely its use as a determinant of employee compensation packages. Employers often claim to utilize a pay-for-performance model. However, principle-agent problems make it difficult for management to identify the varying performance of employees. In numerous settings, employees may have better information about the contributions of peers than management and may be better able to determine appropriate compensation.

Paper two informs the establishment of a corporate prediction market by drawing on employee motivation literature to identify incentive structures and operating processes that best attract and maintain adequate participation levels. We leverage intrinsic and
extrinsic motivation research to examine methods of attracting, and perhaps more importantly, retaining sufficient participation levels. The paper concludes with a series of practical recommendations.

Finally, paper three shares results from a lab-based experiment which tested for the endowment effect within a prediction market. The prediction market run at Hewlett-Packard was set-up such that participants were endowed with some, but not all, securities. It was believed varying portfolios would encourage trade (Plott & Chen, 2002). Research on loss aversion suggests people are reluctant to adjust portfolio holdings they inherit. We leverage lab-based markets to address this perceived disconnect and the broader question of whether an anomaly in the marginal trader behavior would alter the market pricing and volume of trades.

Taken together, the three papers bring the phenomenon to the management literature through discussions of application and limitations. It is hoped that this work will expand the discussion beyond the technical aspects of the markets, and identify opportunities for management researchers and practitioners to leverage prediction markets.
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Chapter One: Introduction

Introduction
Prediction markets were first introduced in the 1980’s at the University of Iowa where economists set up the Iowa Electronic Market to predict the results of political elections in the United States (Tziralis & Tatsiopoulos, 2007). Shortly after that, Robin Hanson began introductory tests on the use of prediction markets (Thompson, 2012). Over the last thirty years, these markets have spread into the corporate world as companies look to harness the wisdom of the crowd to manage their businesses better. Despite adoption at companies like Google, Best Buy, and Hewlett-Packard, these markets are hardly considered mainstream nor are they often discussed publicly by the companies which use them (Thompson, 2012).

My dissertation uses the term corporate prediction market to describe the market-based mechanism used to aggregate information and produce a forecasted probability specifically in a business context. It uses the more general term prediction market when the context is broader and not limited only to business settings. However, these terms are not universal and other authors may refer to the concept as an information market, decision market, electronic market, virtual market, idea future, artificial market, election stock market or political stock market (Tziralis & Tatsiopoulos, 2007).

Krause, Ruxton, and Krause (2009) define prediction markets as a mechanism for leveraging swarm intelligence by allowing people to bet on outcomes or trade shares related to the outcomes. Prediction markets serve as a mechanism for consolidating
individually held information to generate a solution that could not be reached independently (Krause, Ruxton & Krause, 2009).

In their literature review, Tziralis and Tatsiopouls (2007) define prediction markets as:

...markets that are designed and run for the primary purpose of mining and aggregating information scattered among traders and subsequently using this information in the form of market values in order to make predictions about specific future events.

Wolfers and Zitzewitz (2004) suggest excluding “markets where the primary focus is holding or trading risk that may be intrinsically enjoyable.” Additionally, Wolfers and Zitzewitz (2004) exclude markets that are sufficiently large enough to allow for risk sharing and pooling. In other words, the major financial markets are excluded from their work. The focus remains on those markets aimed at consolidating, aggregating and interpreting information collected from traders through a series of transactions. Wolfers and Zitzewitz (2004) do highlight the line can be blurry when determining which markets should be included in the realm of prediction markets. For this dissertation, the focus will remain on markets, leveraged by organizations, for the purpose of aggregating information in support of running the business either operationally or strategically.

The introductory chapter serves two purposes. First, it provides a review of prior works, which set the foundation for exploring prediction markets as viable forecasting tools. Within this review is included a summary of market structures and mechanisms. Generally speaking, the accuracy of the forecast is not heavily debated (Fountain & Harrison, 2010) so we do not delve into a deep discussion of market accuracy. Second, the introductory chapter looks to set the stage for the three papers of my dissertation.
Market Structure

Wolfers and Zitzewitz (2004) identified three types of structures for securities within prediction markets, and each structure is associated with a different interpretation of the market price. The most common market structure is a “winner-takes-all” contract in which the price of the security represents the market’s expectation regarding the probability of an event occurring (Wolfers & Zitzewitz 2004). In this case, if a security pays $100 when the event occurs and $0 when the event does not occur, a market price of $45 represents a market expectation of 45% likelihood to occur.

Alternatively, a market can be structured as an “index” where the payoff is tied to the movement of a given data point, such as the percent of market share for a new product. In this case, the market price represents the expected mean value of the outcome (Wolfers & Zitzewitz, 2004). For example, if a security pays $10 for each percentage point of market share a given product takes after it is launched and it is priced at $45, the market is suggesting an expectation of 4.5% market share.

Finally, a market can be structured as a “spread” similar to how many sport bets are structured (Wolfers & Zitzewitz, 2004). This structure is the least mentioned in the literature. Similar to the index structure, these securities address a range of possible outcomes. Leveraging the market share example above, the spread structure would offer securities which pay a fixed amount if the product captured a given percentage of market share or more. In an even-money bet (i.e., winner doubles their money, loser receives $0), the price of the security represents the expectation of the median outcome (Wolfers & Zitzewitz, 2004).
Securities can also be designed to cover the probability distribution associated with an event. The probability distribution of an event (e.g., market share) can be mapped by offering a family of winner-take-all contracts (Wolfers & Zitzewitz, 2004).

The securities can be worded in such a way that they cover contingencies (i.e., the likelihood of X given that Y has occurred). Berg and Rietz (2003) defined the concept of “conditional prediction markets” as those markets that serve the primary purpose of predicting future events conditional on the occurrence of another event.

Aside from how the securities or contracts are designed, the markets can take on different structures. The most common market structure is the continuous double auction, which is the same mechanism the major financial markets use (Chen & Pennock, 2010). In a continuous double auction participants can submit buy orders (bids) or sell orders (asks) at any point, and compatible bids and asks are matched up resulting in a trade (Das, Hanson, Kephart & Tesauro, 2001). A continuous double auction imposes no risk on the market operator as only trades with willing participants are executed, resulting in a zero-sum game (Luckner, 2008).

Similar to the continuous double auction is a call auction where the buy and sell orders are compiled and then executed at a specified time (Luckner, 2008). While this market also poses no risk for the market operator, the delay in trades results in a delay of information aggregation (Luckner, 2008). This structure would not be ideal for corporate prediction markets given the delay in information availability.

Both the continuous double auction and the call auction require a certain level of liquidity for trades to occur and can be significantly impacted by the challenges
associated with thin markets (Chen & Pennock, 2010; Luckner, 2008). Alternative mechanisms have been proposed to overcome the thin market constraints such as Dynamic Pari-Mutual Markets (Pennock, 2004) and Market Scoring Rules (Hanson, 2007). Given that continuous double auctions are the most common in the literature, my dissertation will focus on that market mechanism. Chapter three explores motivating employees to participate in corporate prediction markets as a way of overcoming the thin market problem.

**Accuracy**

Fountain and Harrison (2010) suggest the debate is not about whether prediction markets produce good forecasts, but rather the debate centers on whether the market price accurately represents the average of the aggregate beliefs. Work by researchers associated with the IEM (Berg, Nelson, and Rietz) as well as work by Wolfers and Zitzewitz have produced near-universal acceptance of the superior accuracy of prediction markets, specifically for election forecasting (Erikson & Wlezien, 2008).

In a winner-take-all market, the accuracy is judged by whether the event occurred or not. It is truly an all-or-nothing situation. However, the question of whether the market price accurately reflects the aggregate belief of participants is still open for debate (Fountain & Harrison, 2010). Studies regarding aggregate beliefs have produced different findings depending on the assumptions regarding financial constraints and risk neutrality (Fountain & Harrison, 2010). Fountain and Harrison (2010) ultimately conclude the prices in prediction markets, *in certain circumstances*, represent the aggregate belief of participates well.
Efficiency

While there appears to be a general consensus on the accuracy of prediction markets, little research has been done on the efficiency of these markets (Christiansen, 2007). Much like the literature on accuracy, the larger, well-known prediction markets such as Hollywood Stock Exchange, Iowa Electronic Market, and TradeSports are most common in the efficiency literature (Christiansen, 2007). To address the lack of research on efficiency in markets outside of the larger public ones, Christiansen (2007) ran a series of prediction markets with significantly fewer traders. By leveraging Inking Markets as the software and focusing on the sport of rowing, Christiansen (2007) found even small markets were efficient in aggregating information.

Woerle (2013) leveraged the online prediction market, Intrade, to test the efficiency of the market in incorporating information regarding an international conflict. Woerle (2013) found support for semi-strong efficiency within the market, and concluded the market was able to quickly incorporate both “good” news (suggesting positive outcome) and “bad” news (suggesting negative outcome) while largely ignoring “neutral” news (that with an ambiguous impact on the conflict). Woerle (2013) did not find support for strong efficiency and concluded the market was not aggregating private information. Ultimately, prediction markets do appear to incorporate new information although to what level of efficiency remains unclear.

Applications

The use of these markets has expanded broadly since the first election markets in Iowa. The early success of the IEM in forecasting the winner of a US Presidential election has led to the expansion of the markets into areas such as predicting economic
indicators, business decision making and other political events (Erikson & Wlezien, 2008).

It appears that from 1990 through 2013 the majority of prediction market work has centered on “applications,” but that actual discussion of corporate prediction markets is lacking. Rather the focus has been on well-known markets, such as IEM and the Hollywood Stock Exchange (Horn, Ivens, Ohneberg, and Brem, 2014; Tziralis and Tatsiopoulou, 2007). However, there have been some well-documented cases where prediction markets were employed by either the private sector or the government to support information aggregation and decision making. Companies leveraging corporate prediction markets include, but are not limited to, Hewlett-Packard, Yahoo, Cisco, and General Mills (Varma, 2013). It should be noted that despite success in forecasting sales, Hewlett-Packard abandoned its prediction market (Seeman, Enders, Hungenberg, 2009).

These businesses have found different applications for their markets. Hewlett-Packard and Best Buy have used the market to forecast sales, while Misys used the markets to gain insight into project performance and Rite-Solutions has used prediction markets to develop new products and improve company performance (Thompson, 2012).

Hewlett-Packard is probably one of the most referenced company-specific markets (Wolfers & Zitzewitz, 2004; Thompson, 2012; Varma, 2013). In 1996, Caltech and Hewlett-Packard partnered to explore ways in which information could be aggregated (Plott & Chen, 2002). Rather than open the market up to all employees, select participants were invited to join mostly because it was believed they would bring different elements of information to the market (Plott & Chen, 2002). Despite the risk of thin markets, a double auction was leveraged and participants were given securities and
cash to use to for trading (Plott & Chen, 2002). Ultimately the forecasts generated by the prediction market were more accurate than predictions generated by the ‘official’ forecasts, suggesting the markets worked for estimating future sales (Plott & Chen, 2002). Chapter four addresses an open question raised by this application. In the HP market participants were given varying opening portfolios in an attempt to encourage trading (Plott & Chen, 2002). Although the endowment effect and status quo bias would suggest endowing participants with an opening portfolio would have the opposite affect and actually decrease trading.

Best Buy, another well cited case, reported similar improvements in forecasting (Malone, Laubacher & Dellarocas, 2009; Thompson, 2012). In 2005, Best Buy leveraged a prediction market to forecast the sales between Black Friday (the day after Thanksgiving) and Christmas (Thompson, 2012). In this case the experts were very accurate with estimates, reaching a high of 94% correct on the day before Thanksgiving, yet the prediction market was still able to outperform and produce results which were 98% accurate (Thompson, 2012). The market at Best Buy was funded by the company in the form of play money given to participants; however, the top trader during the period was awarded a $200 gift card (Dvorak, 2009).

Misys Banking Systems, a United Kingdom-based company which provides software for financial and health-care companies, offered contracts which focused on whether a project would be delivered by a specified date and if the critical bugs associated with a software program could be reduced to a given level by a given time (Thompson, 2012). To incentive participants, traders were given play money to use
within the market which was then tracked via a public leaderboard and top performers were given Amazon gift cards (Thompson, 2012).

**Limitations**

The three corporate prediction markets briefly described above leveraged different incentives to encourage participation. Money, prizes, and leaderboards seem to be obvious ways to encourage participants to stay engaged with the market. Chapter three explores the way firms encourage participation in more depth with the focus on the unintended consequences such incentive plans can produce. From a management perspective, the resulting employee behavior associated with participating in the market is of great interest and represents what could be a very large limitation of corporate prediction markets.

While chapter three will review the limitations associated with incentives in depth, this section highlights some of the additional constraints the markets face.

**Theoretical**

Prediction markets have a number of theoretical limitations. Some of the easiest constraints to identify and understand are the limitations associated with the structure of the contracts. In the case of a winner-take-all market, the contracts are structured as binary events which either occur or do not occur. In this sense, there is no possibility of being partially correct¹.

Second, prediction markets rely on the Efficient Market Hypothesis (EMH) holding true. The EMH essentially suggests that at any given time the price of a security (or contract) will reflect all known information (Luckner 2008). The hypothesis is further

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¹ [http://torontopm.wordpress.com/](http://torontopm.wordpress.com/)
broken down into weak, semi-strong, and strong forms. In the weak form, the hypothesis suggests the markets simply reflect all past price and return information (Fama 1970). In the semi-strong form it is suggested the markets reflect all past information and immediately incorporate any new information (Fama 1970). Last, in the strong form, the markets reflect all past and current information but also incorporate insider information and thus reflect all information, regardless of whether it is public or private (Fama 1970). Fama (1970) contends that there is not significant evidence against the weak and semi-strong forms of the hypothesis and that markets do appear to incorporate past information and adjust to reflect new information. He finds only limited evidence to dispute the strong form of the hypothesis (Fama, 1970). While it is generally accepted that capital markets are efficient, it is important to note how critical the concept is to the success of prediction markets. If markets are not efficient and do not fully reflect the information, at least in the semi-strong form, the accuracy of the forecasts derived from the markets are called into question.

The strong form of the Efficient Market Hypothesis relates well to the next theoretical limitation of particular interest: the “No Trade” theorem. Put in the simplest terms, the No Trade Theorem suggests that in a market comprised of only rational traders, no trades will occur. Milgrom and Stokey (1982) suggest that if all rational traders possess the same information, there is no opportunity to trade. It is only when one party has private information, that the party is open to making a trade. However, by demonstrating a desire to trade, that party reveals having some private information. The other traders, being rational, assume the party willing to trade is only doing so because they have information suggesting the trade is profitable. No rational trader is willing to
engage because they expect to experience a loss on the trade. Thus, despite varying information, no trader is willing to engage.

In the strong form of the EMH it is suggested the market will reflect the information held privately. If only those traders which have insider, or private, information are willing to trade, and there is an irrational (noise) trader willing to accept the trade, then the adjusted price of security or contract will ultimately reflect the information held by the insider. In a prediction market, the market requires some traders be uninformed or irrational and thus willing to engage in a trade (Hanson, 2003). These participants enable those with information to profit in the market and thus keep the market liquid. Ensuring liquidity in the market is also critical because if traders are unable to find a willing partner with whom to engage, the market prices are unable to adjust and information is no longer being aggregated. This challenge is known at the thin market problem (Hanson, 2003).

Legal

Despite having demonstrated immense potential value, anti-gambling laws continue to be a major barrier preventing wide-spread adoption of prediction markets in the United States (Hanson, 2003). In 2006, the United States passed The Unlawful Internet Gambling Enforcement Act and, while most likely not the original intent of the law, ultimately further confused the legality of prediction markets (Cherry & Rogers, 2008). Cherry and Rogers (2008) suggest there are a few ways for prediction markets to safely operate without violating the law. Essentially, by focusing on what the act classifies as exceptions to the law prediction markets may be able to operate outside the jurisdiction. First, the act excludes transactions which are governed by the Commodities
Future Trading Commission (CFTC) and the CFTC has been an aggressive agency in regulating prediction markets (Cherry & Rogers, 2008). The agency took action against Tradesports while also granting the Iowa Electronic Market a ‘no-action letter’ (Cherry & Rogers, 2008). Additionally, using virtual (or play) money, which can only be redeemed for further participation in the market or contests may allow for markets to operate simply by avoiding the use of actual currency or tangible rewards (Cherry & Rogers, 2008).

**Participants**

At their very core, prediction markets depend on the knowledge and activity of those participating in the market. To correctly aggregate the information held by the various traders within the market, those traders must behave in a way which accurately reflects the information and beliefs they hold. The most obvious limitation in this case is that participants could intentionally try to manipulate the market by proposing and accepting trades which are not reflective of their information. A full discussion of potential participant malice is outside the scope of this review, although it is definitely an area worthy of further investigation.

Even if traders were not attempting to manipulate the market, there is a risk that the interface or the market structure may be too complex for novice traders. Hankins and Lee (2011) proposed a mobile based application, FishMarket, to explore the usage of prediction markets within an organization. Over a series of design iterations and pilot studies it was determined for the market to succeed it would need to be accessible to novice traders (Hankins & Lee, 2011).

There may also be a reflection of biases within the market. One such bias, that has been well documented, is the favorite-longshot bias where unlikely events are over-
estimated and likely events are under-estimated (Snowberg & Wolfers, 2010). While this phenomenon historically has been shown in horse-betting, the same problem can arise within a prediction market. This irrational bias for betting on a long-short could potentially drive the price of the contract up, thus skewing the results of the market.

Another participant bias within the market may be a tendency for optimism. Studies at Google found that new employees demonstrated a stronger sense of optimism for Google product sales, and also this bias was stronger on days when Google’s stock price was increasing (Cowgill, Wolfers, & Zitzewitz, 2009)

Google also reported that employees who were located in close proximity to each other tended to behave similarly and when employees moved to new locations their behavior changed to match that of their new neighbors (Cowgill et al., 2009). This suggests employees are sharing information but may not be independently processing the information resulting in possible ‘group-think.’

**Conclusion**

While much work remains to be done in regards to fully understanding corporate prediction markets, I believe the foundation for such work exists. The establishment of the *Journal of Prediction Markets* in 2007 signaled a growing interest, as well as growing body of literature, in the area. Researchers have shown that the pricing mechanism of the market can be used to aggregate information and generate a prediction. Case studies, such as Hewlett-Packard, show the market even outperforms experts. Green, Armstrong, and Graefe (2007) compared prediction markets to the Delphi technique and found “that in situations where markets are feasible they have some advantages over Delphi. Markets should be superior for short-term problems that are easy to address, when it is possible
and desirable to involve a large number of participants, and when the primary goal is obtaining a group response.” It is from this starting point – that, in certain situations, prediction markets are good (if not great) forecasting tools - I believe the conversation needs to evolve.

Chapter two provides an expansion of the policy futures market proposed by Jackson and Sumner (2006). A theoretical model is developed which explores using a corporate prediction market to inform wage setting and staffing levels given a future production target. This chapter aligns with the current cultural push for transparency in wage setting and offers a groundbreaking approach to setting wages and staffing. The model is most useful in a context when co-workers have better information than managers regarding appropriate wages and staffing levels.

Chapter three offers a more practical contribution through a discussion of market incentives and operational design. We address the challenge of sustained trader participation by identifying ways in which firms can appropriately leverage extrinsic motivators and foster intrinsic motivation. The chapter adds value through the informing of practice on how to successfully operate a corporate prediction market.

Finally, chapter four focuses on the specific question of how the way a market is established influences the end result. Typically, in a corporate setting, the company provides employees with currency, and possibly shares, to establish an opening position for the markets. Work done in behavioral economics would suggest that endowing participants with securities would bias the market pricing and trading behavior of participants. However, in the corporate prediction market run at Hewlett-Packard endowing participants was used as a way to encourage trade. Chapter four examines
whether the presence of the endowment effect in the marginal trader alters the pricing or volume traded within the market. This chapter makes significant contributions to behavior economic literature because it directly tests whether an anomaly at the individual level has impacts at the market level. It is also valuable to both researchers and practitioners since it answers the open question if the method in which a prediction market is opened has direct influence on the forecasts generated by the market.

When research on a given phenomenon is scarce within the literature, one does need to question if the lack of publications indicates the topic is not worth exploring. In the case of Corporate Prediction Markets, we would suggest the lack of management-oriented publication should not be viewed as a sign the topic is not worthy of investigation. While economists have long studied the pricing mechanism in markets they have not fully explored the use of markets as a tool within a business context.

The following dissertation makes a contribution to the prediction market literature both through the expansion of prior works (e.g., policy futures markets, endowment effect, and status quo bias) and the combination of motivational literature with the corporate application of prediction markets. In additionally, the dissertation sets the groundwork for future research both in the area of application (context in which a corporate prediction market could apply) and limitations (what biases might be displayed by traders given specific market structures and security designs).
Chapter Two

Introduction

Over the last 35 years or so there has been growing ‘cross-over’ between the fields of management and economics. Specifically, economists have increasingly focused on problems of interest to strategic management scholars who have embraced the ‘language and logic of economics’ (Rumelt, Schendel, Teece 1991). Prediction markets offer a prime example of an economic tool that lends itself to applications in the field of management. Prediction markets are grounded in efficient market theory and exploit the ability of the pricing mechanism within markets to incorporate and reflect information available to those participating in the market. Economists have historically focused on lab-based and theoretical applications of a market and demonstrating the market prices are able to efficiently incorporate new information. Building on this concept, prediction markets trade securities that are designed to directly solicit information regarding some future event or state. This is useful in a variety of settings because firms often need to make decisions today that position the company for the future.

Jackson and Sumner (2006) explored the application of such a market to address challenges associated with central banks. They proposed a market which would trade on policy futures and, given a number of requirements are met, could be used to set the current policy instrument to achieve a future policy target. The model developed was demonstrated to remove the need for Federal Reserve to develop a formal model of the economy. However, if the Federal Reserve utilized private sector forecasts, it could face a circularity problem whereby if the forecasts they receive from the private sector are “too accurate” they receive no feedback because the model would forecast the exact
policy target value, and hence provide no useful information to policymakers. The proposal by Jackson and Sumner eliminates the circularity problem by providing an explicit forecast of the market contract, and an implicit forecast of the policy instrument setting needed to achieve the goal.

In this paper, we look to extend to a broader class of applications the model proposed by Jackson and Sumner (2006), namely to address challenges faced by managers in business settings who must often make decisions based on incomplete or imperfect information, and with delayed results. Similar to Jackson and Sumner (2006) the models are illustrative and are meant to demonstrate the theoretical possibility of applying prediction markets to in the context of business decision making problems. There are a number of ways in which the model can be deployed, however we illustrate two potential contexts which might be of specific interest to managers: suitable wage setting, and determining the appropriate number of hours or workers delegated to a task. Researchers have historically concentrated on understanding the relationship between CEO pay and performance with little attention paid to worker compensation despite the importance of worker compensation to firms (Van Herpen, Van Praag, & Cools, 2005). Further motivating the paper is the cultural push to close the wage gap and increase transparency associated with how wages are set.

Our paper is structured as follows. Section 2 provides a brief introduction to prediction markets. Section 3 proposes two scenarios where a prediction market can inform management regarding wages or staffing needs. Section 4 acknowledges the limitations of the model and section 5 concludes.
Prediction Markets

Prediction markets were initially introduced at universities in the United States in the late 1980’s with the goal of predicting specific events. Many give credit for the first prediction market to the University of Iowa and the Iowa Electronic Market (IEM) which was built to forecast the outcome of political elections (Leutenmayr, Bry, Schiebler, & Brodbeck, 2011; Tziralis & Tatsiopoulos, 2007). In essence, prediction markets facilitate the consolidation of individual information in order to generate a solution (probability estimate) which could not have been reached by any one person acting independently (Krause, Ruxton, & Krause, 2009). In their prediction market literature review, Tziralis and Tatsiopoulos (2007) define prediction markets as:

...markets that are designed and run for the primary purpose of mining and aggregating information scattered among traders and subsequently using this information in the form of market values in order to make predictions about specific future events.

Additionally, as highlighted by Luckner (2008), prediction markets can provide situational information and evaluate decisions over time making them useful as a decision support system. While the simplest form of prediction markets are structured as a ‘winner-take-all’ with the event of interest being a binary outcome (e.g., security pays $1 if Obama wins the 2012 presidential election and pays $0 otherwise); markets can also be structured conditionally, where the event of interest is contingent on some other event occurring (e.g., security pays $1 if Obama wins the 2008 Democrat Nomination, given that Hillary Clinton does not withdraw from the race prior to February 4, 2008, and pays $0 otherwise). Both the simple form and the conditional form of prediction markets can serve in decision support (Berg & Rietz, 2003). Returning to the previous hypothetical
situation: Firm A may be interested in the probability of Firm B launching a product before the end of the second quarter – in which case a simple market would be appropriate. Firm A may also be concerned with what its sales in the third quarter will be, given Firm B launches the competing product in the second quarter – here the conditional market comes into play.

Prediction markets rely on the price mechanism to aggregate information (Leutenmayr et al., 2011). As pointed out in the work of Hayek (1945), the required information, which would allow for a solution to be logically worked out, is never given to a single mind, but rather spread among individuals in the form of incomplete, and possibly contradictory, knowledge. It is through the price mechanism in the market that “knowledge is communicated and acquired” (Hayek, 1945).

There has been some debate over whether the price in a ‘winner-take-all’ market with a binary event truly reflects the average belief of participants (Manski, 2006). Yet this concern appears to have been addressed by the work of Wolfers and Zitzewitz (2006) in which they find

...that prediction market prices aggregate beliefs very well. Thus, if traders are typically well informed, prediction market prices will aggregate information into useful forecasts. The efficiency of these forecast may, however, be undermined somewhat for prices close to $0 or $1, when the distribution of beliefs is either especially disperse, or when trading volumes are somehow constrained, or motivated by an unusual degree of risk-acceptance.

Even when the price deviates from the average belief, the dispersion is relatively small, and prices still reflect the aggregate opinion of participants (Wolfers & Zitzewitz, 2006). Adding to the benefits of prediction markets is the fact the markets allow for
“continuous, direct and timely participation of people” (Leutenmayr et al., 2011). In fact, the accuracy of a prediction market-based forecast is rarely debated at this point (Fountain & Harrison, 2011).

Despite public success stories in business applications from the likes of Google, Hewlett-Packard, and Best Buy, prediction markets have failed to reach mainstream status (Thompson, 2012). Companies, like Inkling Markets, and stories, like the one done by NPR on the Government-run prediction markets are helping to make prediction markets appear more conventional. Ultimately prediction markets have the ability to facilitate a variety of strategic decisions, especially when they involve uncertain events.

For example, when it is difficult for management to monitor, or even observe, employee contributions they can leverage prediction markets to gather the insight from colleagues who may be better positioned to understand others’ contributions, as fellow employees work and interact with one another on a day-by-day basis. Those in management may often find themselves disconnected with the day-to-day workings of an office or division, thereby relying on reports from supervisors to make key decisions, which can be biased, or leave out important details or context about the needs of a project or contributions that employees make (or don’t make).

**Model & Applications**

The framework we use to address these common business challenges borrows from Jackson and Sumner (2006). First, a market is established where participants are able to trade contracts that (at maturity) are equal to the ratio of next period’s policy

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2 Based on conversation between the author and employee of Inkling Market (4/29/15)
3 http://www.npr.org/blogs/parallels/2014/04/02/297839429/-so-you-think-youre-smarter-than-a-cia-agent
target, that is influenced with a lag and the policy instrument effecting current activity.
In our case the policy target is a set level of output or productivity and the policy
instrument is an input which directly influences productivity or production, such as
aggregate wages or staffing levels. In order for such a market to be effective, a target (or
goal, say for production or productivity) must be announced in advance of trading, along
with an intention to use the policy futures price at equilibrium in setting the policy
instrument. Once trading completes, the current policy instrument (wages, or staffing
levels) is set equal to the ratio of announced policy target and the current market value of
the policy future. In their model, this mechanism is employed precisely under the
assumption that the Federal Reserve’s (Fed) model may be flawed and that individual
participants collectively provide more accurate information about the state of the
economy. This approach also reduces the amount of information required by the Fed
thus lowering costs and it is still shown to be an efficient model. In this section, we
expand the application of their model to demonstrate its applicability to the challenges of
wage setting and staffing levels. We also provide an illustrative example of the model in
both contexts.

The proposed model can in theory, be used in multiple ways to address similar
challenges faced by managers when individuals possess information that is unknown or
unobservable to the managers. We develop the model using the example of setting
effective wages when resources (headcount) are fixed in the near-term. We then illustrate
how the model could be applied to establishing headcount requirements in a context
where the desired output is fixed (known). Setting effective wages and staffing levels is
critical to firm success. Employees which are not adequately compensated for their
efforts will ultimately seek employment elsewhere or withhold effort, becoming increasingly disengaged from the firm. Inadequate staffing levels can result in employee burnout as they are asked to take on more and more to compensate for the shortage of workers.

Our proposed model and its applications are built upon a number of assumptions, which are worth briefly elaborating. First, we are assuming management is unable to know the level of effort required to accomplish the goal or produce the desired output. Second, we assume employees, to varying degrees, will behave opportunistically or withhold effort when possible. Third, we assume a positive relationship between wages and effort.

**Model Development**

In our first example, the market is used to determine the efficient wage rate. In the context of this paper we use the term efficient wage rate to refer to the amount of payment an employee must receive in order to produce the required amount of output. Setting wages appropriately for workers is a challenge for multiple reasons. In the case of skilled knowledge workers, managers are often unable to determine the level of effort workers are exerting. Challenges such as this are often described as agency problems, where the agency relationship refers the employment of a person (agent) by another (principle) to perform some service on their behalf and some decision-making power is delegated to the agent (Jensen & Meckling, 1976). This model could be applied to a variety of contexts ranging from corporate attorneys tasked with contract review, to engineers tasked with troubleshooting software post-deployment. Setting appropriate wages is critical to business success, to the extent that employees’ work effort is
commensurate with their pay. In a review of meta-analyses by Gupta and Shaw (1998), they concluded that money is a reliable method for encouraging increased productivity. A study by Wiley (1997) found that for 50 years “good wages”\(^4\) has been ranked in the top five motivating factors for employees regardless of demographics (e.g., gender, age, occupation). Setting wages appropriately becomes increasingly important with highly skilled and highly mobile employees. Variable pay has long been explored as a method for resolving agency problems as the ‘pay-for-performance’ (PFP) compensation plan can help align agents with the principal's goals. However, pay-for-performance can negatively affect performance when a large amount of pay is at risk and when the PFP incentive is removed (Maltarich, et.al, 2017). Furthermore, in many high-skilled professions PFP could result in unintended outcomes. For example, if a corporate attorney is rewarded based on the number of contract negotiations she completes in a given timeframe, she has an incentive to only focus on the easiest (fastest) negotiations and to reach a settlement as quickly as possible, which might not be in the best interest of the firm. While PFP works well for salespersons and piece-rate production, the nature of many high-skilled professions do not align well with a primary PFP compensation plan.

Agents, especially highly skilled workers, also receive a base salary quasi-independent of their performance. This base-salary also serves as a method of motivating effort as the risk of losing the base-salary (i.e., getting fired) encourages employees to perform at least at the minimum level required (van Herpen, van Praag, Cook, 2005). More generally, the following approach to wage setting may be appropriate under the following conditions: (i) When firms must commit to setting wages in advance of work

\(^4\) "Good Wages" is the term used through the Wiley (1997) when discussing satisfactory pay levels.
performed, (ii) when there is imperfect monitoring of worker contributions or production, (iii) when withholding effort is hard to detect, meaning workers generate an output but it is less than the level of production they could achieve if they did not withhold effort.

To address this specific context, we propose a contract with a value (at maturity) equal to the ratio of next period’s target output or productivity goal, and the instrument input, in this case aggregate wages for a team. For the purposes of our model we assume the team is more than one person. We have identified three methods for how the market input can be put into practice. First, all team members can be paid equally, meaning the aggregate wages are evenly divided. Second, the team members can determine, among themselves, how to allocate the money. Third, management can provide discretion in distributing the money amongst the team. A comparison of the three methods is outside the scope of this paper, and we make the assumption firms will rely on management to determine individual wages. Using a market to set the wages for an individual may raise additional concerns related to market manipulation, cultural acceptance and the general sense of ethical practices. A market is established to facilitate the trade of said contract.

Here, we modify the model of Jackson and Sumner (2006)\(^5\) to demonstrate the efficiency of such a market. In this context, the traded market contract is denoted as \(M\), is defined as\(^6\):

\[
(1) \quad M_{t+1} = Y_{t+1}^* - I_t
\]

\(^5\) The full model is presented in Appendix 3.
\(^6\) All variables are expressed as first differences of logs.
where $Y$ represents the level of production or output, $I$ represents the labor-related input (in this example wages), and the subscript denotes the period of time. Valuation of the contract is assumed determined by the following process:

$$M_{t+1} = s_t + \alpha I_t + \epsilon_{t+1}$$

where $s_t$ is a state variable known to forecasters and reflects all the external elements which can impact worker production. For example, employees may be aware of things in the office which hinder productivity such as slow copy machines, limited access to supplies, or supportive (or inefficient) management. Also reflected in the state variable are factors such as the general work condition (comfort of work stations, speed of network, etc.), which can impact efficiency for employees. A limited number of conference room or space to collaborate may negatively impact production and would also be reflected in the state variable. If some team-members need to travel and ‘lose’ a day of work flying to or from the office each week, that would be reflected in the state variable as well. Employees that are able to work remotely may demonstrate greater productive capacity all else equal because they can continue after-hours from home. The state variable is assumed to be known by participants within the market because they experience these conditions daily but may not be known to management because management is removed from the daily experiences of workers.

To illustrate, management may be unaware that teams lose the first 5-10 minutes of each meeting trying to find a space to get into a conference room and set up. This loss of productive time is known to employees and reflected in $s_t$ while management may not have accounted for this on its own. Additionally, $\alpha I_t$ shows the impact of the labor-
related input (wages) on productivity and $\varepsilon_{t+1}$ is a white noise term with mean-zero error. The noise term includes such unforeseen (unforecastable) factors on productivity and effort such as the effects of weather, sick days, or other unforeseen circumstances. For example, if employees must travel to the office each week and there is bad weather which delays flights and negatively impacts output that would be reflected in the noise term. Conversely if the bad weather prevented people from leaving work (i.e., stranding them at work over the weekend) productivity may be positively impacted as the employees unable to return home for the weekend will presumably end up working more.

Encompassed within $\alpha$ are factors such as the level of shirking, work ethic and monitoring which directly influence the impact of the labor-related input on productivity. It is assumed employees are better able to observe teammates’ work ethic and can better account for this when estimating $\alpha$.

We assume the firm uses its target for production or productivity ($Y^*$) and the market forecast $M^f$ to determine the level of labor-related input required:

$$I_t = Y^*_{t+1} - M^f_{t+1}$$

Thus, given a target level of output or productivity announced in advance, and the market-determined value of the futures contract $M$, the input $I$, can be set accordingly. It is worth reiterating, management does not need to know the value of the state variable(s) nor does it need to know the value of $\alpha$ since the information required to set the labor-related input is revealed through trading by $M^f$. The appendix shows the rational expectations equilibrium solution worked out which arrives at the following result:

$$Y_{t+1} = Y^*_{t+1} + \varepsilon_{t+1}$$
Thus, under such a trading mechanism, the future level of production $Y$ (or productivity) is equal to the announced target $Y^*$ plus some random, white noise error. The implication is that the market outcome is therefore the most efficient way to determine the input, in this case wages.

**Wage Setting**

To illustrate how this model would work in the context of setting wages for a team of skilled knowledge we use an illustrative example of contract lawyers within a firm. Often other department rely on the team of specialized workers to provide a ‘service’ which helps the firm obtain goals. For example, sales and procurement rely on contract attorneys to review proposed deals and participate in the negotiation. Management is unable to monitor the productivity of these specialized workers because oftentimes management is not able to know how long a task takes or what is involved in completing it. For example, senior management may not know how long a contract review takes an attorney nor do they know all the work required to complete the task. The skilled worker is able to “game the system” and withhold effort because management is unable to detect shirking. Since management is generally unable to determine the effort required for task completion they are not able to fully evaluate a skilled worker’s contribution. In this illustrative case, the firm would announce an average target turn-around-time for any document sent to legal, knowing some contracts will take longer and some will take shorter. The time it takes to complete any given legal review will depend partially on the level of shirking among attorneys as well as their willingness to work extra hours to meet a deadline. Since other similarly skilled workers are familiar with the tasks required to produce an outcome, they are better positioned to determine if colleagues are withholding effort.
To illustrate, assume the firm expects the average time for a document to be reviewed is 48 hours. The legal team consists of 10 members; each being paid $100,000 annually, or $1 million in total. Knowledgeable employees, those knowing what level of effort is required to achieve a 48-hour goal, are aware that the attorneys will need to put in considerable effort to achieve this goal. These traders believe the total cost for 10 attorneys to achieve this goal is $1.25 million annually. The market will forecast the contract value as 80 (assuming wages are reflected in millions). Management can then use this to calculate the appropriate wages (100 ÷ 80 = 1.25) where 1.25 is interpreted as millions. The firm would then need to increase current aggregate wages by $250,000 to achieve the desired output. We use the example of contract attorneys, but we could have used the context of auditors, engineers, computer programs, business analysts, consultants, or a suite of other highly skilled professional service jobs.

We should also note the amount wages increases by is not an arbitrary number. If we assume the relationship between wages and the market forecast is upward sloping (it does not necessary need to be linear) then an increase in wages will result in an increase in the value of the market contract. More specifically the exact increase in wages, as forecasted by the market, will produce the exact production level desired.

**Employment Setting**

The same logic applies in the second application we explore. As alluded to earlier, the market could also be used to forecast hours or staffing requirements. Similar to the wage setting example, output may require more people rather just better motivated
individuals\textsuperscript{7}. We again use an anecdotal example to illustrate how the model would work; in this case: the headcount requirements for an R&D project team. When the firm announces its production (or productivity goal) the open question is how to staff in a way that achieves this goal. For example, a pharmaceutical team has announced the target of three (3) cancer-treating drugs by the end of the year. This issue here is not how much effort employees are exerting, as the team setting will help mitigate the risk of shirking to some degree, but rather an issue of how many resources are available to focus on the goal. The level of shirking which occurs would be accounted for in the state variable and would assume to be fixed as wages are also fixed. Management, which may not know the level of shirking occurring nor the team dynamics contributing to more/less output, is unsure how to staff the project and may simply opt to \textit{throw more resources at the problem}. There is the risk of over-staffing, as well as understaffing. Employees working on the project are better positioned to determine the staffing requirements given the announced production or productivity target. In our example, assume the market estimates the R&D team needs nine employees to achieve this goal. The market will forecast the value of the market security to be $1/3$, and the contract should trade at this level. The firm can then use this estimate of productivity and its announced goal of three drugs to solve for the staffing requirements ($3 \div \frac{1}{3} = 9$). Again, we used an anecdotal example here of a pharmaceutical R&D team, but the model could apply to any project team. Other examples include teams of programmers developing software, teams of

\textsuperscript{7} We assumed increased wages would increase output or effort amongst employees. In this context we assume the output is dependent on additional resources rather than increased effort amongst current resources and assume wages are fixed and predetermined.
engineers and architects designing infrastructure, or marketers launching a new ad campaign as just a few illustrative examples.

**Limitations**

This approach to setting wages or employment levels is not without limitations. In this section, we address some of the potentially most significant. First, we acknowledge that traders within the market may not be able to fully calculate the value of the state variable and the subsequent market-generated forecast could include additional noise or variance. Second, we explore the risk of market manipulation if employees seek to leverage the market-generated forecast to improve their situation at work. In addition, the situation in which employees are able to influence their own, or a colleague's, wages presents an obvious potential ethical challenge. Finally, we explore the broad issue of cultural acceptance for the market. The notion of cultural acceptance differs from ethical challenges in that the market may not violate any ethical principles but could still be viewed as taboo or socially unacceptable.

**Noisy Forecasts**

The first limitation of the model is the potential noise associated with market participants being unable to forecast the state variable, $s_t$, perfectly. In this case, traders/co-workers may not have a very good idea of the underlying attributes of the worker or the work environment that the worker or team endures. To the extent that there is too much noise in these forecasts from market participants, it may not be advantageous for the firm to use the market-generated forecasts, as they would reflect too much variability; intuitively, they may become so noisy that it is more efficient for management to simply use a ‘best guess’ than a very noisy market forecast. Jackson and Sumner (2006) proposed a solution to this issue through the introduction of a policy
reaction coefficient (PRC), which is used to determine if the firm should attenuate the use of market forecasts given its level of tolerance for noise. The PRC allows the firm to ignore some of the signal from market participants if their forecasts are known to be consistently noisy or inaccurate.

Under this scenario we assume market participants are unable to forecast the value of the state variable, $s_t$, with precision, so the forecast also includes an error term:

$$M_{t+1}^f = E_t(M_{t+1}|s_t) + \eta_{t+1}$$

Following Jackson and Sumner (2006), we add a policy reaction coefficient, $\phi$, such that when $\phi = 0$ the firm ignores the market forecast entirely. The original model implicitly assumed $\phi = 1$. Under this scenario, the firms would then set the instrument as:

$$I_t = Y_{t+1} + \phi M_{t+1}^f$$

Firms will need to determine under which conditions they chose to ignore the market-generated forecast. However, it can be shown that as long as the noise associated with the forecast “is small relative to the noise generated by the state variable, it is optimal to continue using the forecasts.” The appendix demonstrates the equilibrium with noisy forecasts.

**Market Manipulation and Ethical Issues**

Market manipulation represents another potential limitation of the proposed model and applications. In theory, the market could include employees trading on a contract that directly impacts their situation at work. Assuming employees fully...
understand and believe that the market forecasts will be used to set labor-related inputs, they may try to influence the market for personal gain. In the case of the project team, traders in the market could over-estimate the number of employees required to complete the project, and thus, the firm would overstaff which is costly. Employees assigned to the project would reap the benefits of additional resources such as a reduction in required effort as the work would be more broadly dispersed.

One method for addressing this risk is to exclude traders who are directly impacted by the market-generated forecast from trading in the market. Excluding participants would prevent them from revealing their knowledge through trade and is an unnecessarily extreme response to the possible risk of manipulation. Chakraborty and Das (2014) found market manipulation possible in small markets, specifically their “worst-case” scenario of a market with only two participants. Wolfers and Zitzewitz (2004) found that prediction markets quickly corrected for manipulation and prices were only affected for a short “transition” period. Hanson and Oprea (2009) suggested that having a manipulator within the market could actually improve overall performance. Anyone trying to manipulate the market acts as a noise trader and those with ‘correct’ information has an opportunity to profit from the ‘incorrect’ behavior of the manipulator. The firm should encourage employees from a variety of areas to enter the market and thus mitigate the risk of a single trader being able to significantly move the market price and influence the forecast. Alternatively, the firm could opt to only use the forecasts if some minimum level of trades or traders is met.

In the case of the skilled knowledge workers, the risk of increased personal wages is further mitigated by the fact the market is trading on the aggregate sum of all
wages. Any manipulation would serve to increase (or decrease) the total sum of wages paid to the group of workers, but the market would not provide forecasts on required personal wages. Said differently, if the team of engineers consisted of 10 members and each was paid $100,000 annually, the total wages would be $1 million. If the market suggested wages needed to be $1.25 million to achieve the desired target for production with 10 employees, the firm would still need to decide if they should evenly distribute the $250,000 among all engineers or if they should allocate the money differently. The risk of an individual manipulating the market to alter their own, or a coworker’s, pay is somewhat mitigated because traders do not trade on individual salaries.

**Cultural Acceptance and Taboo**

Cultural acceptance has been a potential issue for prediction markets especially in specific contexts. For example, in the early 2000s, the United States Government began investigating the use of prediction markets for cases which would be of interest to the Department of Defense (Hanson, 2006). The market which the government was working to develop was shut down abruptly in the summer of 2003 following very public criticism, as the market was deemed morally repugnant. The majority of criticism surrounding the U.S. Government market was centered on the context of the market and the nature of events which the market focused on (i.e., assassinations, military casualties). The market proposed within this paper (hopefully) avoids the risk of being "morally repugnant," yet the concept of allowing workers to directly influence wages and staffing levels may still be viewed as taboo.

Depending on the culture of the firm, the idea of team members having direct (or indirect) influence on wages and staffing levels may cause unease among managers and
even workers. If upper management is openly supportive of the markets and demonstrates a willingness to utilize the forecasts generated by the market, participants may feel more at ease with participating.

**Concluding Remarks**

We have shown through two illustrative cases how the model proposed by Jackson and Sumner (2006) could be expanded beyond the monetary policy of a central bank and used by firms to address challenges associated with labor-related decisions when management has incomplete information and can be better informed by coworkers. We offer two applications for the proposed model; one where the firm is able to adjust staffing levels by reassigning resources to a project and one where the firm is unable to adjust resource levels but is able to adjust wages.

If firms are able to meet the necessary requirements (i.e., announced production output targets, the establishment of a market to trade contracts, and general acceptance by participants that the forecasts generated would be used), then there seems to be a case in support of leveraging prediction markets within a firm to help address labor-related decisions. Additionally, we address the possibility of market failure due to noisy forecasts and manipulation. We conclude that both challenges can be adequately addressed within the proposed model and thus neither should be seen as deterrents for the firm. We also discuss the ethical implications of allowing employees to participate in a market used to set wages as well as the need for the firm to establish a culture accepting of the market.

While the model described has been shown to theoretically inform staffing and wages, there is still the taboo nature of using one in practice to overcome. From a
practical perspective it is unclear if firms could actually implement and utilize a prediction market successfully to gather information and inform wage setting or staffing levels. Nonetheless, this paper is a starting point to demonstrate the feasibility and applicability of such a market to support such consequential business decisions that often occur under incomplete information by those decision makers.
Chapter Three

Introduction

To be successful, businesses need to proactively make decisions today, which will position them well for tomorrow. Decisions regarding where to build the next storefront, when to launch a new offering and what level of inventory is needed on hand are all made prior to the firm having complete information. In order to make the best possible choices, firms require quality and actionable information about the future. By casting a wide net, firms are able to acquire a large amount of data for consideration. However, handling the diverse, and possibly contradicting information requires tools to help make sense of all the puzzle pieces. Prediction markets, also referred to as decision markets or information markets, leverage the pricing mechanism to consolidate information into probability estimates of future outcomes. De Castro and Cramton’s (2009) study of prediction markets forecasting electrical load demands concluded prediction markets were successful in consolidating and conveying the necessary information for generating a forecast. The generation of predictions by such a market is facilitated by information collection and aggregation; participants reveal information through their trading behavior.

We use the term market to refer to the mechanism in which individual securities are bought and sold. Firms may have numerous markets running concurrently housed within the larger marketplace. Each individual market requires informed traders to reveal valuable information and “noise” traders to provide liquidity in the market and accept the exchanges proposed by “knowledge” traders. Regardless of the number of informed traders, some uninformed, misinformed, or purely noise traders are required to engage in trade with participants with valid information. The market can only aggregate information through the pricing mechanism associated with trades. A market of purely
rational and well-informed traders will quickly freeze because no participant would be willing to make a trade. The No Trade Theorem suggests that in a market comprised of only rational traders, no trades will occur. Milgrom and Stokey (1982) suggest it is when one party has new, private information, that this party will become open to making a trade. However, by demonstrating a desire to trade, that party reveals having some private information. The other traders, being rational, assume the party willing to trade is only doing so because they have information suggesting the trade is profitable. No rational trader, knowing the other traders are rational, is willing to engage because they suspect they would only lose. Thus, despite varying information, no trader is willing to engage. Again, the market would fail to adjust to information because no trades occur and the pricing mechanism cannot signal the new information. Corporate prediction markets are at a higher risk of lacking true noise traders engaging only for "fun" or relying on a “hunch” in that they often consist of a smaller pool of traders who, presumably, are well positioned to be knowledgeable. Thus adequate participation in these markets is critical to its effectiveness by ensuring a diverse information set among participants and helping to mitigate any potential for market manipulation.

Corporate prediction markets are typically open only to employees of the firm, and therefore businesses are constrained by the size of their staff. McHugh and Jackson

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8 We do not make any assumption regarding which employees may have identical information nor do we make assumptions regarding which employees may have reached the same conclusion based on their information. We only highlight that employees who both wish to buy [sell] are unable to trade with each other.

9 In practice, traders do not know who they are trading with and thus cannot determine if they should be suspicious of the trade based on the participant. We simply highlight theory which suggests if a market is fully made up of rational traders, participants would be suspicious of any proposal to trade. That said, in practice the occurrence of this is extremely unlikely, if not impossible.
(2012) found a limited incremental benefit when markets exceed a minimum of 10 – 20 participants, presumably because the incremental traders do not bring a significant increase in relevant information to the market and therefore do not improve the price-based predictions. Thus it is entirely possible for a single market to run successfully with a relatively small number of traders; however, for the market to adjust to new intelligence, participants must be actively engaged and continuously re-balancing (buy/selling) their holdings for the pricing mechanism to fully incorporate the new information. Given that markets can function with a relatively small number of active traders; it seems the greater challenge faced by companies is the need to ensure adequate participation levels which allow the market to continuously incorporate new information. Rieg and Schoder (2011) highlight maintaining engagement among participants as a key challenge for corporate prediction markets. We pause to highlight here that individual markets may function with 10-20 traders, but the overall corporate prediction market (i.e., the larger marketplace) will require 10-20 traders per individual market. It seems unlikely that a single group of 10-20 traders would be sufficiently knowledgeable in all areas of interest (i.e., individual markets on diverse subjects). Thus the corporate prediction market[place] will require some number of participants in excess of 20, which allows for an adequate number of knowledge and noise traders in each individual market.

We draw on prior work regarding intrinsic and extrinsic motivation, specifically cognitive evaluation theory (CET), to evaluate various programs designed to attract and engage participants in corporate prediction markets. We leverage CET because the theory offers insights on how an extrinsic reward (i.e., performance in the market) affects the intrinsic motivation an individual may have (i.e., internal desire to participate in a
market). Prior literature has suggested a suite of prediction market incentive structures and operational guidelines, which can serve as extrinsic motivators and/or foster intrinsic motivation to participate. While some participants will be drawn to a financial reward, others may feel the relatively small (in comparison to salary) amount of cash is not attractive enough to justify the effort. We review prior approaches and evaluate them through the lens of CET to consider the expected impact they would have on continued participation in corporate prediction markets. Our focus is on addressing the question of how to attract and foster sustained engagement among traders, as this must be dealt with if firms wish to continue the pursuit of corporate prediction markets as a viable tool for knowledge gathering and planning purposes. Initially attracting participants to sign-up and place an opening trade is not enough for the markets to be valuable to the company. Participants must continue to adjust their portfolio of securities in accordance with new information for the pricing mechanism to fully capture and reflect the changing knowledge of traders.

The remainder of the paper is organized as follows: in section 2 we review prediction markets. In section 3 we review the literature on employee motivation with regard to knowledge sharing and CET. Section 4 discusses and evaluates incentive structures and general operating practices for corporate prediction markets. Section 5 we consider how cultural difference, specifically individualism and collectivism, may influence engagement levels among employees. In section 6 we conclude.

**Prediction Markets**

Prediction markets, like all markets, represent a collection of traders engaged in a series of buying and selling transactions. Specifically, prediction markets center on the
exchange of securities structured such that their values are tied to the future outcome of an event. Given the relative newness of prediction markets, particularly outside the field of economics, they warrant at least a brief discussion.

Prediction markets began gaining popularity in the 1980’s with the most famous market being the Iowa Electronic Market (IEM) at the University of Iowa. The IEM primarily focuses on forecasting the outcome of political elections. Political elections provide a straightforward context for illustrating prediction markets and their use. The most common structure for securities within a prediction market is known as winner-take-all (WTA), where a security pays a predetermined amount if a given event occurs and pays nothing otherwise. In a winner-take-all market, the price of the security represents the market’s expectation regarding the probability of an event occurring (Wolfers & Zitzewitz, 2004). For example, starting November 14, 2014, the IEM opened a winner-take-all market related to the 2016 US Presidential Election. Two securities were offered. The first security paid $1 if the Democratic Party nominee received the majority of votes cast between the two major parties; it paid $0 otherwise. The second security paid $1 if the Republican Party nominee received the majority of votes cast between the two major parties; it paid $0 otherwise. As of November 1, 2016, the share that paid in the event the Democratic Party nominee received the most votes was trading at $0.62, and the share that paid in the event the Republican Party nominee received the most votes was trading at $0.396. This translated to a collective estimate of a 62% chance the Democratic Party nominee would receive the majority of votes while the Republican nominee had roughly a 40% chance of receiving the majority of votes. It

10 https://tippie.biz.uiowa.edu/iem/markets/pres16.html
does not speak to the percentage of votes received by either party, but rather the likelihood a given party would receive the majority of the popular vote (as opposed to winning the Electoral College). In this case, the market forecasts were correct and while the Republican nominee won the election, the Democratic nominee received the majority of the popular vote.

Markets like this have also been applied in corporate settings, with companies like Hewlett-Packard, Google and Best Buy using prediction markets for a variety of forecasting purposes. The focus of prediction markets can range from sales forecasting to identifying new product release dates (Bothos, Apostolou, & Mentzas, 2008). In one of the most referenced corporate prediction markets (Thompson, 2012; Varma, 2013; Wolfers & Zitzewitz, 2004) Hewlett-Packard partnered with California Institute of Technology to explore information aggregation methods (Plott & Chen, 2002). A market aimed at forecasting future product sales, and structured in a winner-take-all format, ultimately produced predictions which were more accurate (closer to reality) than those generated by the ‘official’ forecasting team (Plott & Chen, 2002).

Experimental, academic, public, and corporate prediction markets have leveraged different methods to maintain engagement, ranging from real money to grant funding to leaderboards and other prizes. The well-known Iowa Electronic Market allows participants to invest US currency but caps investment at $500 per participant (Berg & Rietz, 2006). In a market opened to pediatricians, nurses, microbiologists and others with presumed knowledge of influenza cases, traders were provided with $100 in ‘FLU’ currency and at the end of the experiment any FLU money they had accumulated was converted to educational grants (Polgreen, Nelson, Neumann, & Weinstein, 2007).
Participants at Ford enjoyed earning bragging rights among their peers as well as being recognized via published results based on their successes in internal prediction markets (Montgomery, Stieg, Cavaretta, & Moraal, 2013). At Google, employees reportedly were motivated by the tee-shirts they could win by performing well in the market (Cowgill, Wolfers, & Zitzewitz, 2009).

Google runs what is believed to be the largest corporate prediction market and is open to active employees along with some contractors and vendors. Cowgill et al. (2009) reported roughly 6,500 accounts with around 23% of those accounts placing at least one trade. Of the roughly 20,000 employed by Google at the time, approximately 7.5% had made at least one trade within the market. In reporting on the markets at Google, Cowgill et al. (2009) take special care to highlight the employees participating in the market were not representative of the employee population. Participants had been with the company longer, were less likely to leave the firm, and were more embedded within the organization. It appears that employees who were presumably well positioned to succeed in the market were the employees opting into the market.

Plott and Chen (2002) highlight the importance of selecting knowledgeable traders for corporate prediction markets to ensure those employees with the most valuable information are able to reveal it in the market. A diverse background among traders suggests independent decision-making and unique information, both of which add to the strength of the forecast (Surowiecki, 2005). Corporations will, therefore, need to encourage a broad range of employees to engage with the market. However, as discussed earlier, initially attracting employees to the market is not as significant of a challenge as maintaining engagement.
Intrinsic and Extrinsic Motivation
In terms of motivating an employee to continuously take part in the corporate prediction market, we focus on two types of motivating factors – extrinsic and intrinsic. Extrinsic motivation is supplied by environmental incentives, meaning the desire to engage in [avoid] behavior is driven by a desire to obtain [avoid] some external factor. External motivation often follows a “do X in order to get Y” or “do X in order to avoid Z” type reasoning (Reeve, 2014). Corporate prediction markets, by their nature, leverage extrinsic motivators in so much as markets require a participant to purchase shares they believe profitable in order to increase the value of their portfolio, particularly when the growing value of the portfolio translates into perceived rewards. It is worth taking pause here to clarify the extrinsic motivation we consider inherent to the market. We make clear distinction between the act of the trading shares (i.e., the buying and the selling) and the act of engaging in the market. The former is a requirement of the latter, but the terms are not synonymous. The act of trading refers to physically placing [responding to] trades. An employee could be completely unaware or indifferent to the value the firm derives from the market and trade solely for the purpose of maximizing their return. Engaging with the market, as we define it, means the employee is consciously aware of the value the market has for the firm and chooses to participate. It is entirely possible to engage with the market for a suite of reasons not limited to the extrinsic motivators directly linked to successful trading activity.

Firms have the ability to offer extrinsic rewards or punishments to encourage employees to undertake additional tasks outside of formal job requirements, such as active trading within a corporate prediction market. Rewards can include financial incentives such as cash payments, material goods such as prizes, or intangible benefits
such as praise and recognition (Bartol & Srivastava, 2002). As noted above, prediction markets lend themselves to numerous forms of rewards ranging from cash to public acknowledgment of strong performance. While extrinsic rewards can produce the desired effect at first, they are generally unable to sustain the behavior in the long run (Gerhart & Fang, 2015).

Extrinsic motivators may also carry the risk of corruption, also known as the crowding out effect. It is realized when a reward is offered for a task and, in the long run, the individual will only perform the job in exchange for the reward – essentially, the introduction of an extrinsic reward has crowded-out any internal desire to perform previously present (Osterloh & Frey, 2000). In the context of a prediction market, this crowding out effect may manifest with traders only willing to participate when the prizes or profits associated with the market are sufficiently large enough to warrant the effort. Extrinsic motivators may, in the short run, be sufficient to promote the act of trading within a corporate prediction market.

Engaging in a corporate prediction market requires the employee to be aware of the benefit the firm derives from the market and thus the behavior, to some degree, is altruistic. The employees’ participation is driven by something outside of the rewards associated with market performance.

Ryan and Deci (2000a) define intrinsically motivating activities as those that satisfy needs for competence, autonomy and/or relatedness with motivation arising from within the individual. Firms may enhance the intrinsic motivation associated with an activity through environmental conditions only if the task originally held some intrinsic interest or value to the employee (Ryan & Deci, 2000a). Said differently, organizations
cannot make prediction markets intrinsically interesting to employees who have no inherent interest in participating, although a firm can attempt to position the market in a way that would resonate with employees. For example, if the firm stresses the contribution employees are able to make to the overall success of the organization, employees may participate because they are interested in helping the company despite having no inherent interest in markets or trading. Firms can also attempt to encourage employees to internalize goals by fostering a sense of autonomy, competence, and relatedness (Ryan & Deci, 2000b). We believe, if structured correctly, firms can attract participants through offering extrinsic rewards, but also promote internally motivated traders to continue to engage.

Feelings of competence, or skill mastering, can be fostered through an extrinsic reward, such as praise, only when coupled with a sense of autonomy (Ryan & Deci, 2000a). In this case, autonomy refers to an internal locus of causality, or to actions that are believed to be self-selected (Deci & Ryan, 1985). Corporate prediction markets, which allow employees to opt-in and trade as much or as little as they choose, can provide a sense of autonomy. Positive feedback has been shown also to enhance intrinsic motivation where criticism has been demonstrated to diminish it (Ryan & Deci, 2000a). Said differently, an external factor – feedback – can influence intrinsic motivation via its effect on individuals’ sense of competency. Additionally, the feedback inherently provided in the market, through the profits or losses generated, can potentially help employees gain a sense of growing competency and skill in trading. Hagger, Koch, and Chatzisarantis (2015) found that participants who received positive feedback while solving a puzzle opted to continue working on the puzzle more than participants who
received no feedback on their puzzle solving performance. The recognition of good performance following an activity lead to increased time spent on the activity. Applying this finding to corporate prediction markets we would expect participants who receive positive feedback regarding their performance to demonstrate a higher level of engagement than those receiving no feedback.

Ryan and Deci (2000b) proposed a continuum of motivation spanning from amotivation (i.e., a lack of action or just going through the motions) to intrinsic motivation where extrinsic motivation lays between the two. We acknowledge there may be some participants who will remain unmotivated and never engage. We suggest, in the subsequent section, focusing on creating an environment where as many participants as possible are able to internalize the motivation will help drive participation to the maximum level possible. When extrinsic motivators are internalized, the individual is motivated by personal factors, but the motivation is not truly intrinsic because it continues to depend on external factors (Vallerand et al., 1992). For example, if a firm encourages participation in a market, employees may be extrinsically motivated to participate with the logic being: I trade in the market because my boss told me to. As the employee begins to internalize the motivation, the logic may shift to I trade in the market because it’s what good employees do. Finally, the employee may reach a level of self-determined behavior where the logic is something like I trade in the market because I feel good when I help the company or I trade in the market because it is important to me (Ntoumanis, 2001). When the individual has internalized the motivation and self-determines their level of participation, the behaviors demonstrated are closer to intrinsically motivated behaviors with limited need for external incentives.
Extrinsic motivation is needed when the task is not of natural interest, and some other motivation is required to generate action (Reeve, 2014). When presented with opportunities to increase a sense of relatedness to others, increase perceived competency, and increased autonomy, it is expected individuals will better internalize and integrate the activity (Ryan & Deci, 2000b). Corporate prediction markets can leverage extrinsic rewards to attract initial interest from employees, and then if successfully designed, foster a shift from pure “if-this-then-that” motivation and encourage participants to achieve and be motivated by internal satisfaction obtained through participating.

**Motivation and Corporate Prediction Markets**

The nature of prediction markets, specifically the use of a ‘currency’ to facilitate trade and the subsequent rewards and recognition associated with performance in the market, provide a context in which to explore the impact of various motivational factors on employee behavior. In this section, we compile a list of incentives and operational approaches to running a corporate prediction market and evaluate how each performs as a means of motivating continued participation.

**Extrinsic Motivation**

We begin our evaluation with the incentive of cash. In a ‘cash-based market’ participants ‘invest’ money and they are able to withdraw profits from the markets. We use the term ‘invest’ loosely, as most corporate prediction markets are funded by the firm and employees are not putting their personal finances at risk. The Hewlett-Packard markets gave participants roughly $50 to use in their corporate prediction market for trading (Kiviat, 2004). Ho and Chen (2007) recommend a compensation of $500 for participation, although it is unclear how they determined this value. Coincidentally, $500
is the maximum value a trader can invest in the IEM (Malone, 2004) and appears significantly higher than what firms report spending on internal markets (Cowgill & Zitzewitz, 2015). While researchers may disagree on the general success of money as a motivator, in the context of the corporate prediction market, cash is likely a weak incentive. The amount of money at play is often insignificant in comparison to salary or other compensation programs. For example, a market profit of $500 represents only half a percent (0.5%) of the average monthly income for an entry-level software engineer at Google.11 Gupta and Shaw (1998) report that management can use financial investments as a way to signal to employees what is important to management. It would then stand to reason that a relatively insignificant amount of money being directed towards the market could be interpreted as a lack of management interest or support.

When cash is offered in exchange for a particular action, it risks crowding out intrinsic motivation, and the task becomes more of a ‘job’ and less of an enjoyable activity. As employees come to expect cash rewards for participating in the markets, firms will need to continually add funds to maintain a level of interest, especially if employees begin demanding more money for participation. Finally, at least anecdotally, the cash incentive is not valued by employees. Bo Cowgill reported that when he forgot to pay the cash prizes at Google, it was not noticed, but when the winners’ tee-shirts did not arrive it was widely recognized (Dye, 2008). We, therefore, discourage the use of a real currency within the market.

11 http://www.payscale.com/research/US/Job=Software_Engineer/Salary/d2f8987b/Google-Inc.-Entry-Level
To facilitate trade, the market will require a virtual currency as participants will need something to use in the exchange of securities. If cash is not used for buying and selling, some cash-alternative will need to be offered [accepted] in exchange for securities. Servan-Schreiber, Wolfers, Pennock, and Galebach (2004) found no significant difference in market performance when the market used real currency compared to virtual. The question then becomes what the virtual currency is worth if anything. We caution against converting virtual currency to real currency, regardless of the exchange rate, since that would effectively turn the virtual currency into real money and the firm would be faced with the same problems associated with real currency. The work of Servan-Schreiber et al. (2004) would suggest cash holds no advantage in the market anyway.

Firms will have a variety of options for how to treat the virtual currency in the corporate prediction markets. Firms could offer some exchange for virtual currency, or they could opt to not include material goods as part of the corporate prediction market. If they opt not to leverage material goods, the firm still has a number of ways to motivate participation.

**Intrinsic Motivation**

Buckley (2016) suggests reputation as a motivator which could be used when incentivizing participants in prediction markets as it offers a nonmonetary individualized incentive. Atanasov et al. (2016) found leaderboards did not distort pricing (e.g., over- or under-confident estimates) which suggests the use of reputational incentives does not negatively impact market performance. By providing positive feedback to the top participants, the firm may be able to foster a sense of competency, which in turn helps
promote intrinsic or internalized motivation. We do caution against publishing a full list of all participants as those at the bottom may become discouraged, which can lead to demotivation, particularly if the market has a significant number of participants.

An alternative method could be to make ranges, or brackets, of the leaderboard available, based on a person’s placement within the marketplace (i.e., across all individual markets within the corporate prediction market). For example, the top 25 traders would only see the top 25 spots; while traders ranked 26 – 50 would see the corresponding 25 spots. This could foster some sense of competition among groups of like-skilled traders and also present the presumably achievable goal of reaching the top of one’s bracket. We recommend the publication of top N traders along with individual bracket leaderboards based on a trader’s performance. For employees motivated by competition, this public ranking may generate interest in achieving ‘bragging rights’ and encourage intrinsic and internalized motivation. However, firms must be cognizant of the issues surrounding competition. Researchers have found evidence of competition fostering as well as diminishing intrinsic motivation (Reeve & Deci, 1996). The bracket-style leaderboard might help avoid the disincentives associated with a game one feels they cannot possibly win. We would suggest showing the top x% of traders publicly which provides reputational benefits for the highest achievers. Participants outside this top x% would see the top performers as well as their personal bracket. Individuals would then be able to see how far they are away from the top spot but the information is relatively private and thus mitigates the risk of ‘public shaming’ or embarrassment by showing everyone the poorest performers.
We suggest firms also leverage some type of material reward in addition to the reputational motivation derived from the leaderboard(s). A McKinsey roundtable suggested rewarding top performers with prizes (Dye, 2008). In this method, the firm would use the overall holdings of the traders to rank them and then reward the top N performers with prizes such as gift cards. Conversely, Siegel (2009) recommended against rewards based solely on becoming one of the top N traders because it removes the incentive for other traders if (or rather, when) the top performer(s) have established a significantly large lead.

Google linearly converted market currency to lottery tickets for a raffle where the approximate prize budget was $10,000 (Cowgill & Zitzewitz, 2015). All participants had a chance to win the lottery, but a strong performance in the market increased one’s likelihood of winning. While it is not explicitly stated how the lottery-ticket and prizes are managed, it seems allowing participants to allocate their tickets into the drawing for prizes of the greatest personal interest may enhance this incentive. The lottery system offers two motivations – first, it provides an incentive to participate since traders are rewarded simply by entering the market. Attracting participants to place just one trade helps introduce noise traders as the reward is not contingent on market performance. Additionally, once the initial trade has been placed, some traders will carry on to more fully engage with the corporate prediction market. Second, traders are rewarded for strong performance, but not directly. Those with better performance have a higher chance of receiving a reward, but do not necessarily receive one. Research has shown directly rewarding behavior could crowd-out intrinsic motivation, but ‘random’ rewards do not generate the same response (Frey, 1994). To put this in the context of a corporate
prediction market, the prizes ‘won’ in the lottery are not guaranteed, nor are they directly tied to performance in the market. Once someone receives a prize (by winning the lottery), he or she is presumed to be more likely to continue the behavior which earned them the reward (i.e., participating in the market). Noise traders, who generally speaking will have worse performance than knowledge traders, still have a chance at rewards, and thus their behavior is also incentivized. Since the prize was not directly contingent on performance in the market, it should not serve as an extrinsic motivator capable of crowding out any intrinsic motivation present.

We conclude the best use for the virtual currency (a.k.a. extrinsic motivator) is to convert it to tickets for a lottery where employees are able to win prizes. Additionally, we believe the bracket-style leaderboard, when participation levels warrant it, would mitigate the risk of demotivating (shaming) poorly performing traders while maintaining the motivation associated with recognition. Bracket-style leaderboards may also serve to foster a healthy level of competition among like-skilled traders and the competition may serve to encourage participation for “the fun of it.”

The operational design and processes associated with the market may also be leveraged to foster intrinsic or internalized motivation. For example, firms will need to determine the frequency and timing of opening / closing markets, what topics the market will cover, and how directly and strongly management supports and encourages participation in the market.

Google “reset” the markets each quarter with employees starting out with equal amounts of virtual currency and new topics to trade on (Cowgill & Zitzewitz, 2015). Siegel (2009) recommends continually introducing new markets as a method of
increasing ‘stickiness’ with participants and demonstrating the marketplace, overall, is active. Current research is relatively silent on whether markets should be launched at set intervals (i.e., new sets of markets launch at the start of each quarter) or if markets should be launched ‘randomly’ when the topic arises or if it makes a significant difference at all. Along the same lines, it is unclear if it is preferable to have the markets close at the same time (e.g., all close at the end of the quarter) or if markets can close at different times. If a firm wants to ‘reset’ markets quarterly, like Google (Cowgill & Zitzewitz, 2015) having markets open and close at set intervals better facilitates this; however, if firms ‘reset’ markets biannually or annually, then having markets open / close in an ad-hoc fashion within the 6-12 month timeframe seems feasible.

When markets are reset each quarter, or at some regular interval, it removes the disincentive associated with a top spot being out of reach. Resetting the market retains the incentives related to a top spot but allows people to have multiple (at each reset) chances at it. Additionally, securing the top spot in one period may encourage the trader to try to ‘reclaim’ the top spot in subsequent periods as a form of reputation-based incentive. We recommend the markets be reset at least biannually to allow multiple chances for participants to claim a top spot. We also recommend firms introduce a new market roughly every month to hold the interest of participants. When new markets are released, participants may be curious enough to log in and see the topics, and once in the market may be more likely to place a trade. Said differently, the new markets would serve to attract participants to the market.
Resetting the markets makes facilitating the lottery easier as well. The lottery
drawings could be held at the conclusion of each market when the virtual currency is
reset for each participant.

Buckley (2016) suggests entertainment value as an alternative motivator which
could be used when incentivizing participants. Google dedicated 30% of its markets to
“fun” topics – those of interest to employees but lacking a clear relation to the business
(e.g., winner of the Baseball World Series) – and concluded the existence of fun markets
might create liquidity in the business-related markets (Cowgill et al., 2009). Markets
regarding topics where there is a considerable ambiguous public information have better-
motivated trade in comparison to markets where a few insiders hold a large information
advantage, regardless of how inherently interesting the topic is (Leigh & Wolfers, 2007).
Predictit.org has consistently found higher trade volumes on markets centered on the
number of tweets (i.e., posts on Twitter) the President (or Vice President) of the United
States has in a five-day span than in markets asking about Congressional Legislation. It
appears the ‘fun’ topic (Presidential Tweets) and the lack of insider information on the
topic attract more participants than the more ‘serious’ market where insider information
is critical.

Ho and Chen (2007) suggest senior management should encourage participation
and management should clearly articulate the importance of the markets in decision-
making. Siegel (2009) echoed this idea as well as the importance of a “pre-launch
campaign” to drive up interest and educate participants. Senior members of the firm
could also take on a role of “champion” essentially becoming the face of the market and
leading by the example of participating regularly (Siegel, 2009). However, the use of
senior management to drive participation may put intrinsic motivation at risk if it is seen as trying to control behavior (Reeve, 2014). In other words, if leadership positions the market as something employees *should* engage with rather than using their communications to inform employees of the market as something in which they *could choose* to participate, employees may feel they have lost some autonomy, and it will be harder to internalize the goal (Reeve, 2014). Done appropriately, the perception of senior management support may help an employee internalize the act of trading when trading is viewed as valued by people the employee respects or feels attached (Ryan & Deci, 2000a). Employees may participate as a way of signaling to management they too value the markets. However, when the market is forced upon employees, they are unlikely to shift the motivation from *I participate because my boss told me to*, towards a more internalized logic of: *I participate because I enjoy helping the company.*

The prediction market creates an environment of relatedness in that traders are connected to each other and engaging in a common activity. Creating a community can help motivate participation by satisfying the intrinsic need to belong.

Up to this point, we have focused on positive reinforcements and fostering intrinsic motivation. There is also the possibility of negative reinforcement for undesirable behaviors, in this case, the undesirable behavior would be not participating in the market. In other words, management could ‘punish’ those who opt out of engaging in the corporate prediction market. In regards to continued participation, Ho and Chen (2007) suggest withholding earnings for traders not meeting some minimum threshold of activity. While we see how the threshold requirements would encourage trading activity, we generally shy away from this method until further research can demonstrate it would
not adversely affect market pricing. If traders are forced to make trades regardless of a change in opinion, the market pricing is expected to become noisier as the signals are not based on new information, but rather required activity.

More importantly, punishment can produce a number of negative side-effects including a damaged relationship between punisher (the firm) and the punishee (the trader) and has been shown to be an ineffective method of motivation (Reeve, 2014). We expect employee markets will realize more success when participation is driven by enjoyment of the activity rather than fear of punishment.

**Corporate Culture & Prediction Markets**

We believe that the culture found within the firm will also play a role in how employees respond to a corporate prediction market. While we believe fostering intrinsic (or internalized) motivation will lead to sustained participation levels, it should be noted the corporate culture may be an indicator of how much of the employee population is easily convinced to participate in the market.

Schwartz and Davis (1981) proposed a closed-loop process in which corporate culture is solidified and strengthened. They suggest the beliefs and values employees hold create situational norms (i.e., behaviors) and those behaviors serve as the basis for further developing beliefs and values. For example, in a firm where participation in the corporate prediction market is the established norm, employees would observe the level of participation among colleagues and conclude that the market must be valuable and thus begin or continue to participate. Of course, for firms looking to launch a corporate prediction market, there is not a pre-established norm of participation.
We, therefore, discourage firms from focusing on creating a culture explicitly supportive of corporate prediction markets to one conducive to the success of a corporate prediction market. Abdul Rashid, Sambasivan, and Johari (2003) explored the relationship between corporate culture, employee commitment, and performance. Their work is particularly relevant because firms experiencing different levels of commitment from their employees will need to consider the general willingness of employees to engage in a pro-social behavior when designing a corporate prediction market. We use the term pro-social behavior loosely to mean employees are engaging in things outside their specific job function for the good of the firm. For example, firms with a culture of helping and employees that generally demonstrate pro-social behavior might be able to leverage a messaging campaign to capitalize on the traders’ intrinsic willingness to help out. By positioning the corporate prediction market as a tool that provides insights for better decision making, employees who are generally willing to help the firm may be more likely to engage because they are internally motivated to help the firm and it is the cultural norm to go beyond explicit job functions if it is for the good of the firm.

Conversely, a firm with a culture of freeloading or general unwillingness to go above and beyond may need to rely more heavily on extrinsic rewards to sustain participation. Moorman and Blakely (1995) suggested that individuals who fall closer to the collectivist end of the individualism-collectivism spectrum are more likely to demonstrate pro-social behaviors. At this end of spectrum the focus is on the success of

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12 A full discussion on culture and values is out of scope for this paper. We have selected two illustrative cultures for the purpose of demonstrating culture is a factor that will need to be considered. The selection of individualism and collectivism was selected as a convenient example of how different values could impact the way employees respond to and engage with the market.
the group rather than the success of oneself. Firms that employ cultural groups that tend to demonstrate high levels of individualism (e.g., the United States\textsuperscript{13}) and firms that overwhelmingly motivate and reward the individualist (e.g., U.S. firms) may struggle to establish a corporate culture of pro-social behavior. In this context, the individual achievements associated with corporate prediction markets (e.g., leaderboards) may be better motivators as employees are more likely to focus on personal gains and are used to their personal performance being rewarded.

**Conclusion**

To summarize, we have leveraged intrinsic and extrinsic motivational research to examine methods of attracting and retaining participants for internal prediction markets. From a practical perspective, firms can leverage this work as a guide for implementation of a corporate prediction market. Specifically, we suggest the use of real money, either directly or through the conversion of virtual currency, should be avoided when possible because of the adverse effects it may have on employees’ ability to internalize the goals of the market. We view the recognition of employee success as a strong motivator that can foster the intrinsic motivation some employees may have. To facilitate motivation markets should be reset to better allow participants a chance at the top spots and that topics should cover both ‘fun’ events and those directly related to the business. Additionally, the firm will need to understand how to best position and message the introduction of the corporate prediction market to fit smoothly within the corporate culture and behavioral norms. Corporate prediction markets can be positioned as both a collective activity for the good of the firm, or they can be positioned as individual

\textsuperscript{13} https://www.hofstede-insights.com/country-comparison/the-usa/
behavior with rewards for performance. While ideally, positioning the market in an altruistic light is desirable, firms with strong individualist cultures may need to rely more heavily on individual awards for achievements to drive the desired participation levels.

This work should be viewed as a beginning step towards understanding corporate prediction markets and how to best deploy them within a firm. We contribute to the growing literature on prediction markets by compiling a list of incentives used in various corporate prediction markets and evaluating each based on its likelihood to foster intrinsic motivation or encourage an internalization of the goal (i.e., participation). We also contribute to the literature on cognitive evaluation theory by applying the framework to a new context.
Chapter Four

Introduction

Prediction Markets, first introduced approximately thirty years ago at the University of Iowa, have proven to be successful forecasting mechanisms in both business contexts (Plott & Chen, 2002) and political contexts (Berg, Forsythe, & Rietz, 1997; Wolfers & Zitzewitz, 2004; Sunstein, 2005). Within a prediction market, participants trade securities that have their values tied to a future outcome. In the most common form, the market price of the share corresponds to the collective probability estimate of the event occurring. For example, in a political market where a share pays $100 if a given candidate wins and nothing otherwise, a market price of $35 would signal a probability of 35% that the candidate wins. The success of prediction markets has encouraged research aimed at practitioners to aid in their implementation. For example, Borison & Hamm (2010) highlight the incentives required to establish a market, and a McKinsey roundtable discussion was held to review how businesses might go about leveraging corporate prediction markets for their forecasting needs (Dye, 2008).

Different prediction markets have been established using a variety of market institutions. The market at Google, which is one of the, if not the, largest corporate versions of a prediction market, was modeled after the Iowa Electronic Market (Cowgill, Wolfers, & Zitzewitz, 2009). In the Iowa Electronic Market, participants purchase bundles of securities which represent all possible outcomes and maintain their value as long as they remain a bundle of securities (Ottaviani & Sørensen, 2007). Alternatively, Hewlett-Packard (HP) established a prediction market by instead endowing participants with various shares, essentially giving different participants different portfolios (Plott & Chen,
According to Plott and Chen (2002), “the unequal distribution of endowments was used to encourage trading by attempting to make sure that the initial endowments of securities did not approximate the ultimate equilibrium.”

Because the HP market gave shares to participants, it may have been susceptible to the endowment effect. This effect, originally discussed by Thaler (1980), refers to the phenomenon that individuals tend to value an item that is in their possession (i.e., that is part of their endowment) too highly because the disutility of losing something that one owns is larger than the utility increase experienced when the same item is acquired.¹⁴

Kahneman, Knetsch and Thaler (1991a) provide evidence of the existence of the endowment effect. In their experiments some students are assigned the role of sellers and are endowed with a good (such as a coffee mug, pen, or chocolate bar). Other students are made buyers and have the ability to purchase a good from a willing seller. Sellers are asked to report the minimum amount they would accept for the good while buyers were asked to report the maximum they would pay for the good. The supply and demand curves are then calculated along with a market clearing price and trades were executed. The authors find that the minimum price students who are randomly endowed with a good are willing to accept to sell it is substantially higher than the maximum price buyers are willing to pay to buy it, and they show that this gap is driven by an increase in the value the sellers place on the good when it becomes part of their endowment. The effect takes place nearly immediately, meaning as soon as a subject is endowed with a good they are susceptible to demonstrating the behavioral anomaly.

¹⁴ The endowment effect is similar to the mere ownership effect in Psychology (see e.g. Beggan, 1992). It is also similar to status quo bias (Samuelson and Zeckhauser, 1988) which encourages agents to stick with their present (default) position. In the present context, this results in a preference for keeping shares owned as a seller and declining to buy shares as a buyer.
In a prediction market like that run by HP where participants are endowed with shares, there is a possibility they will display the endowment effect. If those with the shares demand higher prices than what buyers are generally willing to pay, fewer buyer-seller matches will occur and fewer trades will be executed. Additionally, the pricing in the market will be higher than if sellers were not demonstrating the endowment effect, distorting the prediction that the market yields. While HP was allocating shares to help drive trade, the method could very well have the opposite effect, resulting in inaccurate predictions.

This issue points to a larger question in behavioral economics generally. As Kahneman, Knetsch, and Thaler (1991b) explain, the neoclassical model of how individuals make decisions assumes “that agents have stable, well-defined preferences and make rational choices consistent with those preferences in markets that (eventually) clear.” Many of the behavioral anomalies that have been identified do not impose fundamental challenges to this approach, and can be integrated into the neoclassical framework (Camerer & Loewenstein, 2011), but others pose fundamental challenges to this framework. The endowment effect falls into this latter group since it can result in preference reversals where the optimal choice an individual makes in two situations that are otherwise identical is different based on whether the individual owns the good.

Still, even these more severe challenges to the neoclassical model are benign in the eyes of some critics. The central point of contention is whether they have an impact on market outcomes, i.e., the quantity and price at which trade occurs, division of surplus, and the efficiency of the market. If so, then the challenges need to be taken more seriously. But
if not, then the neoclassical approach is an adequate tool to model and predict how markets function.

For example, Becker (1957) models animus-based discrimination against black employees in a perfectly competitive labor market where employers have varying degrees of distaste for hiring black workers. He shows that in the short run, the wage gap between white and black employees depends not on the average level of prejudice, but on the level of prejudice of the marginal discriminator – the employer who is indifferent between hiring white and black workers given the equilibrium wage level for each group in the market.\textsuperscript{15}

We study whether and how the forecasts yielded by prediction markets can be impacted when some sellers (including the marginal seller) are vulnerable to the endowment effect using simple lab experiments. Markets of 3 buyers and 3 sellers trade shares of a security that have a 50 percent chance of paying off and a 50 percent chance of being worthless. The security pays if, at the end of the experiment, a fair coin flip results in heads. Participants are told upfront how much they would receive for each share of the security that they possess should the coin flip result in heads.

We run two experiments with different market conditions but the same predicted equilibrium. In Experiment 1, the three sellers are given three shares each of the security to sell, and they receive $1.60, $2.00, and $2.40, respectively, for each share of the security that they own when the market closes if the coin flip is heads. The three buyers in the market receive $2.20 per share if the coin flip is heads. The predicted equilibrium in this

\textsuperscript{15} In the long run, since less prejudiced employers earn higher profits by the virtue of paying lower wages to their employees, they are more likely to survive and expand, and discriminating employers are competed out of the market. Anomalous participants are less likely to leave prediction markets since participants do not enter or exit over time due to competitive pressures in the same way.
market is a price of $1.10 and a quantity of 6. In this equilibrium, the $2.00 seller is the marginal seller: the seller whose choice to sell or not determines the location of the equilibrium.

We compare two treatments where one seller is induced to have an endowment effect to a control group where no seller is induced. In Treatment 1, to induce an endowment effect, the marginal $2.00 seller is given a bonus of $0.20 for each share of the security they still hold when the market closes. In theory, this should lower the equilibrium quantity to 3 since the bonus should make the $2.00 seller unwilling to sell at the equilibrium price of $1.10. In Treatment 2, this endowment effect bonus is instead given to the non-marginal $1.60 seller. This raises the lowest price at which this seller should be willing to sell, but not enough to make them unwilling to sell at $1.10, so it should have no impact on the market equilibrium.

In Experiment 2, we adjust payments for sellers to $1.00, $2.00, and $3.00 and increase the size of the endowment effect bonus to $0.50. The predicted equilibrium in this market is the same as that of Experiment 1, and the predicted effects of the induced endowment effects are also the same in each treatment. However, since the difference between the security values for each seller and the size of the endowment effects are larger, it should take larger departures from theoretical behavior to result in deviations from the predicted outcomes.

The results of the experiments are surprising. Even when the marginal seller is vulnerable to the endowment effect, which should theoretically result in a decrease in the equilibrium quantity, we observe almost no effects on the market outcomes, even when the endowment effect is large in Treatment 2. Sellers who experience an induced endowment
effect sell slightly fewer shares of the security, but the effects are not large enough to impact the overall market quantity or price which remain close to what theory predicts when no endowment effect is present.

There are multiple implications of this research. First, we add to the literature on decision-making biases, specifically testing for the effect within prediction markets. To the best of our knowledge, this is a new application and prior research has not tested for the effect in this context. Second, we contribute the prediction market literature in two significant ways: (a) we identify and test for a bias which, theoretically, could significantly reduce the validity of the predictions generated and (b) we provide insight regarding how to initiate a prediction market.

The remainder of the paper proceeds as follows. Section II describes the experimental design. Section III presents theoretical predictions of what the outcomes of the markets should be. Section IV describes the data and results. Section IV concludes.

**Experimental Design**

We conducted two lab-based experiments with undergraduate student subjects at Bentley University. A total of 396 subjects participated in the two experiments. These subjects are randomly assigned roles as buyers or sellers in prediction markets where the good being exchanged is shares of a security that have a 50 percent chance of paying the subject an assigned amount and a 50 percent chance of being worth $0. Whether the security pays is determined by a coin flip. Subjects are paid their assigned value for each share of the security that they hold at the end of trading if the coin flip is heads, and the shares are worthless if the coin flip is tails.

The trading mechanism of the markets is a double auction with no resale so that the theoretical prediction of the market outcomes can be easily identified. The markets are run
by computer using a trading procedure that is based on the GIMS program (Palan, 2015) written for the z-tree software platform (Fischbacher, 2007).

Table 1 presents critical details of the design. Each market has six traders with three buyers and three sellers.\(^{16}\) The subjects participate in two markets each, yielding 132 market-level observations. When possible, we ran sessions with 24 subjects divided into four markets.\(^{17}\) In Experiment 1, each of the three sellers is paid a different amount for each share of the security that they hold: $1.60, $2.00, or $2.40 if the coin flip is heads. These values are intentionally close together to allow us to study markets where small deviations from how the subjects should behave in theory can have big impacts on the average price at which trades occur, the quantity that is exchanged, and the sellers who participate in transactions. All three buyers receive $2.20 for each share of the security that they own if the coin flip is heads.

In Experiment 2, the setup is similar but the values of shares of the security are more spread out: if the coin flip is heads, sellers 1, 2, and 3 (hereafter referred to as the $1.00 seller, the $2.00 seller, and the $3.00 seller, respectively) receive $1.00, $2.00, and $3.00 respectively for each share of the security that they hold when the market closes. As in Experiment 1, all three buyers receive $2.20 for each share of the security that they own if the coin flip is heads.

\(^{16}\) Plott and Chen (2002) used between 7 and 26 participants in the markets run at Hewlett-Packard. While markets with more traders are attractive because they are better able to overcome liquidity issues, markets with more than 21 traders have been shown to demonstrate a level of over-confidence (Christiansen, 2012). Additionally, Christiansen (2012) found markets with fewer than 15 traders were calibrated but there was a risk of under-confidence (or lower prices). Given the lab setting and limited frame for trading (5 minutes per market) we found no significant liquidity issues with the market and, in general, participants were able to execute trades.

\(^{17}\) Subjects were recruited from economics classes and the sessions were run during normal class times. On occasion when fewer than 24 students were in the class, fewer markets were run.
In each experiment, markets are assigned to either a control group or one of two treatments. In Treatment 1, the seller with the middle value for shares of the security, $2.00, is given a bonus for each share of the security that is not sold. The bonus is $0.20 in Experiment 1 and $0.50 in Experiment 2. This bonus is an induced endowment effect: it artificially increases the value the seller places on the shares with which they are endowed by directly giving them more money if they do not sell the share. We then compare the outcome of the treatment markets with this endowment effect in place to the control markets, which operate without any induced endowment effect.

At each session of four markets, the 24 subjects were first randomized into one of four groups, and within each group, the six subjects were randomized into the various buyer and seller roles. All groups first participated in a practice round to gain familiarity with the interface, then played two rounds on which their payment could be based. At the end of the experiment, we flipped a coin to decide which round payment would be based on. Each group played one round under Control conditions with no endowment effect in place, and one round under one of the treatment conditions with an endowment effect-inducing bonus given to one of the sellers. Group 1 played a Control round first, and a Treatment 1 round (where the $2.00 marginal seller was given the bonus) second. Group 2 played a Treatment 1 round first and a Control round second. Group 3 played a Control round first and a Treatment 2 round (where the $1.00/$1.60 seller was given the bonus) second. Group 4 played a Treatment 2 round first and a Control round second. This design allows us to use within-subject variation to identify how markets in a Treatment condition operate differently than markets under the Control condition, while controlling for order effects.
In each market, buyers were given $6 to spend on shares of the security, while sellers were given 3 shares of the security and $3. Buyers were able to spend as much or as little of the $6 as they wished and sellers were able to retain or sell as many shares of A as they had available. Once a buyer made a purchase he was unable to resell the shares, likewise, sellers were unable to purchase additional shares of A.

At the start of the experiment the administrator thanked students for participating and provided consent forms to all participants. The administrator then verbally went over the details following a script. First, the subjects were told that they would be participating in a market with three buyers and three sellers. Second, they were told that they would be trading shares of a security that had a 50 percent chance of paying them an amount that would be displayed in their instructions, and that whether the security would pay off would be determined by the flip of a fair coin. An online coin flipper was used to flip coins; the screen of an administrator’s computer was projected on the wall so all subjects could see the result of the flip. The online flip was demonstrated, and the class was asked a question as a group to test their understanding of how the coin flip would affect their payments. Students were asked if a share of the security paid them $2.00 in the event of heads and paid $0 in the event of tails, how much a share of the security would pay them on average. Students were allowed to volunteer an answer prior to the administrator, and once a student gave the correct answer of $1.00, the reasoning behind this calculation was explained. Subjects were then told that they would play three rounds of the market, and that their role would be the same throughout the experiment.

Next, to make sure that the endowment effect was salient, the subjects were told that in some rounds, a seller might be given a $0.20 (or $0.50) bonus for each share that
they did not sell. Screenshots of the portion of the instructions that reflect the presence of
the bonus were shown so that the subjects knew what to look for. Finally, a screenshot of
the market interface was displayed, and examples of how to use it were explained. The
experiment then began. The computer interface displayed detailed instructions regarding
the details of the market, the subject’s role, how much they would be paid for each share
of the security they owned at the closing of the market if the coin flip was heads, how their
payment is calculated, and for sellers, whether they would be given the bonus for each
unsold share. These instructions were shown before the market opened, and remained on
the screen during the round. Appendix 3 shows screenshots of the instructions that were
provided before the beginning of the experiment, and Appendix 4 shows a screenshot of
the market interface for a seller who is given the bonus.

The markets remained open for five minutes. Between each round, sellers were
reminded verbally to check to see if they would be given the bonus in the next round. At
the conclusion of the three rounds, a coin was flipped three times for each of the four
markets. The first coin flip determined the value of the security in round 1, the second coin
flip determined the value of the security in round 2, and the third determined which round
(1 or 2) would be used for payment - heads correlated to the first round and tails correlated
to the second round. After the coin flips, payment was made to each participant.

**Theoretical predictions**

Figure 1 displays the supply and demand curves for Experiment 1 assuming all
agents are risk neutral and the market is perfectly competitive. Panel A shows the situation
under Control with no endowment effect in place. For the supply curve, the $1.60 seller is
willing to sell all three of their units at any price higher than $0.80, the $2.00 seller is
willing to sell all three of their units at any price above $1.00, and the $2.40 seller is willing
to sell all three of their units at any price above $1.20. Thus, the total quantity supplied is 0 for all prices below $0.80, 3 for all prices above $0.80 but below $1.00, 6 for all prices above $1.00 but below $1.20, and 9 for all prices above $1.20. For the demand curve, the quantity demanded is 0 for prices above $1.10 and is as many as the buyers can afford for prices below $1.10; we will treat this quantity as 15, the number affordable at $1.10, for simplicity. The resulting equilibrium is a quantity exchanged of 6 and a price of $1.10. Among these six sales, three are predicted to be sold by the $1.60 seller and three are predicted to be sold by the $2.00 seller. The $2.40 seller is predicted to sell no shares.

Panel B shows the situation under Treatment 1 where the $2.00 seller is given the $0.20 bonus for each unsold share. In the terms of Becker (1957), the $2.00 seller is the “marginal” seller whose behavior theoretically should determine the market equilibrium. This induced endowment effect raises the minimum price that the $2.00 seller must receive to be willing to sell their three shares to $1.20. As a result, the $2.00 seller becomes unwilling to sell at the predicted equilibrium price of $1.10, and the total quantity supplied falls to three for prices between $0.80 and $1.20. The portion of the supply curve that changes as a result is red. The predicted equilibrium quantity falls to three, while the predicted equilibrium price remains $1.10. The three sales are predicted to be made by the $1.60 seller.

Panel C shows the situation under Treatment 2 where the $1.60 seller is given the $0.20 bonus for each unsold share. This induced endowment effect raises the minimum price that the $1.60 seller must receive to be willing to sell their three shares to $1.00. As a result, the total quantity supplied is now 0 for prices between $0.00 and $1.00, but the
predicted equilibrium quantity and price are the same as those under Control since the $1.60 seller should still be willing to sell at the prevailing market price of $1.10.

Figure 2 displays the supply and demand curves for Experiment 2, again assuming all agents are risk neutral and the market is perfectly competitive. The situations under Control, Treatment 1, and Treatment 2 are similar to those in Experiment 1. The price ranges for each quantity supplied are different due to the different payments the sellers receive from owning shares of the security, but the predicted equilibrium quantity and price are the same in each treatment.

Panel A again shows the situation under Control. For the supply curve, the $1.00 seller is willing to sell all three of their units at any price higher than $0.50, the $2.00 seller is willing to sell all three of their units at any price above $1.00, and the $3.00 seller is willing to sell all three of their units at any price above $1.50. Thus, the total quantity supplied is 0 for all prices below $0.50, 3 for all prices above $0.50 but below $1.00, 6 for all prices above $1.00 but below $1.50, and 9 for all prices above $1.50. The demand curve is the same as in Experiment 1. Despite the supply curve changes, the resulting equilibrium is again a quantity exchanged of 6 and a price of $1.10.

Panel B shows the situation under Treatment 1 where the $2.00 seller is given the $0.50 bonus for each unsold share. This induced endowment effect raises the minimum price that the $2.00 seller must receive to be willing to sell their three shares to $1.50. Thus, the total quantity supplied is now 3 for prices between $0.50 and $1.50. The portion of the supply curve that changes as a result is red. As in Experiment 1, the predicted equilibrium quantity falls to 3, while the predicted equilibrium price remains $1.10. The three sales are predicted to be made by the $1.00 seller.
Finally, Panel C shows the situation under Treatment 2 where the $1.00 seller is given the $0.50 bonus for each unsold share. This induced endowment effect raises the minimum price that the $1.00 seller must receive to be willing to sell their three shares to $1.00. As a result, the total quantity supplied is now 0 for prices between $0.00 and $1.00, but as in Experiment 1, the predicted equilibrium quantity and price are the same as those under Control.

Table 1 summarizes the predicted equilibrium prices and quantities, the number of shares that are predicted to be sold by each seller, and the expected profits earned by each seller type and by the buyers in each treatment of each experiment. Although the differences between the seller security values and the size of the induced endowments effects are substantially larger in Experiment 2 than in Experiment 1, the predicted equilibria, and how the equilibria are predicted to change in response to the endowment effects, are exactly the same in the two experiments. This allows us to compare the impact of endowment effects across two markets where the effect is larger in one case but the predicted impact on market outcomes is the same.

**Data and Results**

Tables 2A and 2B present summary statistics of the key variables from our experiments. Surprisingly, the raw data suggests that, in both experiments, the endowment effect had little to no impact on market outcomes. In both experiments and in all treatment groups, the quantity traded is close to the expected quantity of 6 shares. In Experiment 1, the average price for a share was slightly higher than the expected value of $1.10; with the control average being $1.17 and the treatments having an average of $1.11 and $1.19. Experiment 2 produced slightly higher prices ranging from $1.19 to $1.25. In both
experiments the highest average prices occurred when the marginal trader ($2.00) was subjected to the endowment effect, but the differences are small.

The control groups in both Experiment 1 and 2 produced results close to what theory would suggest. As shown in the previous section, we expect 6 shares to trade for an average price of $1.10. In Experiment 1 an average of 6.11 shares were traded at an average price of $1.17, while in Experiment 2 an average of 6.71 shares traded with $1.23 being the average price. The expected profits of buyers and of all three seller types are also very close to their theoretical predictions. Given the control group produced results very much in line with theory, we take this as evidence that simply giving some participants three shares does not produce a natural endowment effect apart from the one that we experimentally induce.

The reason the prices and quantities are so similar across the treatment groups appears to be driven by the sellers' behavior. Sellers minimally, if at all, alter their behavior when presented with the endowment effect. In Experiment 1, both the $2.00 seller and the $1.60 seller sell slightly fewer shares when they have the endowment effect, as expected, but not enough to lower the total quantity sold. The $2.00 seller sells 2.05 shares when the endowment effect is present versus 2.26 shares in the control. The $1.60 seller sells 1.59 shares when the endowment effect is present versus 2.23 shares in the control. The slight reduction by the sellers is not large enough to change the average quantity sold.

In Experiment 2, when the $2.00 seller in Experiment 2 is subject to the endowment effect, the overall quantity traded does drop from 6.71 in the control to 6.19 shares. However, this change is nowhere near as large as theory predicts (dropping from 6 shares to 3 shares). This small change is driven again by the behavior of sellers. The $2.00 seller
reduces the average shares sold from 2.16 in the control to 1.75 when the endowment effect is present, whereas theory predicts that this seller would sell 0 shares.

Additionally, in both experiments, the high value seller ($2.40 or $3.00) does engage in trade which prevents the market quantity from falling too much. In theory this seller should engage in no trades, but since they do and they are never given the induced endowment effect, the overall impact of the effect on the total quantity traded is smaller than expected.

Summary statistics of the behavior of each seller type yield additional insights. In Experiment 1, the presence of the endowment effect had little impact on how active the sellers were in the market. Sellers made slightly fewer offers when given the endowment effect bonus. The $1.60 seller made an average of 3.12 offers when the endowment effect was present and between 4.23 and 6.16 when it was not. The $2.00 seller made an average of 2.61 offers with the endowment effect and between 2.67 and 3.42 when not receiving the endowment effect-inducing bonus. In Experiment 2, the seller with the endowment effect made slightly more offers than in the control. The $1.00 seller made 4.40 offers with the effect compared to 3.97 in the control. The $2.00 seller made 3.27 with the endowment effect compared to 3.23 offers in the control setting. Regardless of the endowment effect, sellers continued to make offers for selling which contributed to the prevention of quantity dropping between control and treatment.

These raw averages, while interesting, do not take advantage of the design of the experiment which allows us to measure the impact of the endowment effects using two observations from the same group of participants, thus holding constant differences in, for
example, the risk preferences of the subjects. To accomplish this, we run OLS regressions of equations of the following form:

\[ Y_{ij} = \alpha + \beta_1 T_{2ij} + \gamma_j + \epsilon_{ij} \]  \hspace{1cm} (1)

where \( Y_{ij} \) is the outcome of interest (e.g., quantity traded, market price, the quantity sold by each type of seller, and the expected profits of each type of seller and the buyers) for group of six subjects \( i \) in market group \( j \), \( j = 1 \) or 2 for the two markets each subject group participates in; \( T_{1ij} \) is a dummy variable that equals 1 if the $2.00 seller has the endowment effect in subject group \( i \) and market group \( j \) and \( T_{2ij} \) is a dummy variable that equals 1 if the $1.60 seller (or $1.00 seller in Experiment 2) has the endowment effect in observation \( i \) and market group \( j \), and the control markets, where no sellers have the endowment effect, is the omitted category; \( \gamma_j \) are market group fixed effects, and \( \epsilon_{ij} \) is an error term; standard errors are clustered by experiment session.

Tables 3A and 3B summarize our findings regarding the impact of the endowment effect on market level outcomes (average price, quantity, the number of offers made by sellers, the number of offers made by buyers, and the quantity sold by each seller type) in Experiment 1 and Experiment 2, respectfully. Column 1 of each table shows the estimated impact of the endowment effects on the quantity traded in the market. The point estimates suggest that the quantity sold when the marginal trader (the $2.00 seller) has the endowment effect falls relative to control in both cases; however, none of the estimates are statistically significant. In Experiment 1 we find an estimated decrease in quantity of -0.11 and in Experiment 2 we find an estimated decrease in quantity of -0.56. These effects are statistically significantly smaller in magnitude than the decrease of three predicted by theory \( (p < 0.01) \).
These small decreases can be attributed to the marginal trader making fewer sales in markets where they are subject to the Endowment Effect. These estimates are reported in column 6 of each table. In Experiment 1 we find the quantity sold by the $2.00 seller decreases by 0.28, though the estimate is statistically insignificant. In Experiment 2 we find a decrease of 0.50; the estimate is statistically significant at the 10 percent level. While directionally correct, the estimated effects are again statistically significantly smaller in magnitude than the predicted decrease of three ($p < 0.01$).

As expected, when the $1.60 or $1.00 seller is subjected to the endowment effect there is no significant change to quantity sold in the markets. In Experiment 1 we find a very small decrease of -0.06. In Experiment 2, we find no difference (point estimate of -0.01). In all cases, each effect is statistically insignificant; thus, we are unable to detect a change in quantity given the endowment effect.

The estimated impact of both endowment effects on all other market outcomes—the average price (column 2 of Tables 3A and 3B), the quantities sold by the $1.60/$1.00 seller and the $2.40/$3.00 seller (columns 3 and 5 of Tables 3A and 3B), and the expected profits of each seller and the buyers (columns 6 through 9 of Tables 3A and 3B) are all also small and statistically insignificant.

Table 4A and 4B summarize the impact of the endowment effect on seller behavior in Experiment 1 and Experiment 2, respectively. Columns 1 through 3 report the estimated impact of the endowment effects on the number of offers made by each seller type. In Experiment 1, the point estimates suggest some increased reluctance to trade when a seller is given the endowment effect-inducing bonus for each unsold share. The seller subject to the endowment effect makes slightly fewer offers. The $2.00 seller offers -1.06 fewer
trades while the $1.60 seller reduces offers by -0.41, but neither estimate is statistically significant. Conversely, the findings in Experiment 2 suggest the seller subject to the endowment effect makes more offers, but again, the predicted effects are small and statistically insignificant.\(^{18}\)

**Conclusion**

As a whole, there is little evidence that the endowment effects had any substantial influence on the outcomes of the markets or on the behavior of sellers in those markets. This represents good news for prediction markets in that it suggests despite the induced anomalies in behavior at the trader level, the market produced similar outcomes. Even when sellers were faced with a rather large endowment effect (bonuses representing 10% or 25% of the share value) which could make them less willing to trade, there is little to no impact at the market level. Interestingly, our findings would suggest the way HP established their markets, varying the portfolio of participants, neither increased nor decreased the quantity traded or the prices within the market.

Our findings are also interesting in that they suggest behavioral anomalies, even when found in the theoretically marginal trader, do not significantly alter market outcomes (quantity and price). However, one should be hesitant to take this as evidence supportive of the neoclassical model used to generate predictions. The results are largely driven by sellers acting in ways that are inconsistent with this theory. The $2.00 sellers, for example, appear willing to sell at prices that are not high enough to justify selling. In Experiment 2,\(^{18}\)

\(^{18}\) We understand there may be concern the small sample sizes results in the analysis being under powered. However, with the standard deviations we are able to detect effects as follows: in experiment 1, for the $1.60 seller, a decrease in quantity of 1 with power = 0.797; in experiment 1, for the $2.00 seller, a decrease in quantity of 0.8 with power = 0.836; in experiment 2 for the $1.00 seller, a decrease in quantity of 0.8 with power = 0.790; and in experiment 2 for the $2.00 seller, a decrease in quantity of 0.8 with power = 0.798
when this seller is given the $0.50 bonus for each unsold share, the expected value of a share is $1.50. Yet these sellers sold 1.75 shares on average for an average price of $1.27, which is well below their expected value of their shares.

Theory would also suggest the high-value seller ($2.40 or $3.00) should not trade in the market as they should be unwilling to sell for the rational maximum price buyers would pay. However, in all markets we found the high value seller engaged in 1.5 to 2 trades on average at prices below their rational thresholds (selling for average prices ranging from: $0.99 - $1.33), and they also proactively proposed trades (averaging 2.19 – 4.53 offers per market). In sum, sellers engaged in more trades than was optimal, and this kept the quantity exchanged from falling in the way that theory predicted.
Figure 1. Supply and Demand Conditions in Experiment 1

Panel A. Control

Panel B. Treatment 1

Panel C. Treatment 2
Figure 2. Supply and Demand Conditions in Experiment 2

Panel A. Control

Panel B. Treatment 1

Panel C. Treatment 2
Table 1. Experiment design details

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<thead>
<tr>
<th>Seller security values:</th>
<th>Experiment 1</th>
<th>Experiment 2</th>
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Predicted equilibria (assuming risk neutrality):

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Session Organization (both experiments)

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<td>1.39 (1.14)</td>
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<td>-$0.42 (2.54)</td>
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<td>$1.29 (0.39)</td>
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<td>11.00 (4.84)</td>
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<td>6.16 (9.68)</td>
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<td>Q sold by $3.00 seller</td>
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<tr>
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<td>-$0.81 (2.38)</td>
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<td>Avg P rec’d by $1.00 seller</td>
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Table 3A. Impact of the endowment effects on market outcomes, Experiment 1

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<th>Q sold by $2.00 seller</th>
<th>Q sold by $2.40 seller</th>
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<th>Exp. Profit of $2.00 seller</th>
<th>Exp. Profit of $2.40 seller</th>
<th>Exp. Profit of buyers</th>
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<td>(7)</td>
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<td>(9)</td>
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<td>(0.42)</td>
<td>(0.36)</td>
<td>(0.56)</td>
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<td>0.71</td>
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Table 3B. Impact of the endowment effects on market outcomes, Experiment 2

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<th>Exp. Profit of $2.00 seller</th>
<th>Exp. Profit of $3.00 seller</th>
<th>Exp. Profit of buyers</th>
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<td>(7)</td>
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Table 4A. Impact of the endowment effects on seller behavior, Experiment 1

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<th>Low price offer by $2.00 seller</th>
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Table 4B. Impact of the endowment effects on seller behavior, Experiment 2

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<th>Offers by $2.00 seller</th>
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<th>Low price offer by $1.00 seller</th>
<th>Low price offer by $2.00 seller</th>
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<td>1.94</td>
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<td>(0.76)</td>
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<td>(0.38)</td>
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<td>Yes</td>
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<td>0.86</td>
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Appendix 1: Full Model

Contract value, $M$, at a time one period in the future, is a function of the production/productivity, $Y$, and the labor-related input, $I$

$$M_{t+1} = Y_{t+1} - I_t$$

The future contract value, $M$, can be modeled as a function of the state variable, $s$; the labor input where $\alpha$ represents the impact of the input on production / productivity and a white-noise error term, $\varepsilon$

$$M_{t+1} = s_t + \alpha I_t + \varepsilon_{t+1}$$

We can calculate the value of the input (at current time period) as a function of the announced targeted production/productivity, $Y^*$ and the market forecast value of the contract, $M^f$

$$I_t = Y^*_{t+1} - M^f_{t+1}$$

The market forecast for the contract $M$, represents the value of the contract, $M$, given the state variable, $s$.

$$M^f_{t+1} = E_t(M_{t+1}|s_t) \equiv E_tM_{t+1}$$

Using this rational expectation estimate this is shown to be equivalent to

$$E_tM_{t+1} = (s_t + \alpha Y^*_{t+1})/(1 + \alpha)$$

Or

$$M_{t+1} = \frac{s_t}{1 + \alpha} + \frac{\alpha Y^*_{t+1}}{1 + \alpha} + \varepsilon_{t+1}$$

Using the setting for $M_{t+1}$ it can be shown that actual productivity or production, $Y$, is equal to the stated target plus some random, white noise error

$$Y_{t+1} = Y^*_{t+1} + \varepsilon_{t+1}$$

$$VAR(Y - Y^*) = \sigma^2_\varepsilon$$

The implication is that the variance of output from target is unforecastable white noise
Appendix 2: Noisy Forecast

If the participants are unable to fully forecast the state variable, we assume there is an error term associated with the state variable ($\eta_{t+1}$)

$$M_{t+1}^f = E_t(M_{t+1}|s_t) + \eta_{t+1}$$

The firm sets a value for $\phi$ depending on how sensitive it is to the market forecast. We note here the value of $\phi$ may vary depending on the context of the market and the firm’s willingness to accept the risk associated with noise.

$$I_t = Y_{t+1}^* - \phi M_{t+1}^f$$

As in Jackson and Sumner (2006), the rational expectations equilibrium is:

$$E_t M_{t+1} = (s_t + \alpha Y_{t+1}^*)/(1 + \alpha \phi)$$

Or

$$M_{t+1} = \frac{(1 - \phi)s_t}{1 + \alpha \phi} + \frac{(1 + \alpha)Y_{t+1}^*}{1 + \alpha \phi} - \phi(1 + \alpha) + \varepsilon_{t+1}$$

The variance associated with the actual productivity/production and the announced target is:

$$VAR(Y - Y^*) = [(1 - \phi)/(1 + \alpha \phi)]^2 \sigma_s^2 + \phi^2(1 + \alpha)^2 \sigma_{\eta}^2 + \sigma_{\varepsilon}^2$$

The firm should use the model, regardless of the noise so long as the variance in productivity/production is less than what would occur if $\phi$ was set to 0, or:

$$[(1 - \phi)/(1 + \alpha \phi)]^2 \sigma_s^2 + \phi^2(1 + \alpha)^2 \sigma_{\eta}^2 + \sigma_{\varepsilon}^2 < \sigma_s^2 + \sigma_{\varepsilon}^2$$

The above could be rewritten as:

$$\frac{\sigma_{\eta}^2}{\sigma_s^2} < \frac{2(1 + \alpha) + \phi(\alpha^2 - 1)}{[\phi(1 + \alpha)^2(1 + \alpha \phi)^2]}$$
Appendix 3. Instructions

Screen 1:

Thank you for participating in this experiment in economic decision-making. During this experiment you will be able to buy (or sell) shares of a security within a market. There will be 6 participants in each market, including yourself. At the end of the experiment you will receive compensation based on your decisions within the market. You are free to leave the experiment at any point.

Screen 2 (example for buyer):

This is your first round. You will be compensated for this round.

Click the Market for Security A below the empty right click the market for Security A.

The purpose of this is to help you become familiar with the market interface and trading.

In this experiment you are a buyer in the market for shares of Security A.

At the end of the market your total profit will be the amount shown at the bottom of the screen. In the event that you do not make any profit, you have made a profit of zero shares of Security A.

You will initially have one share of Security A in your account. You may buy or sell shares of Security A within the market. You may trade shares of Security A within the market. You may also purchase shares of Security A within the market. You may also purchase shares of Security A within the market.

You may purchase a buy offer in the market for Security A. You may also purchase a sell offer in the market for Security A. If you accept a buy offer, you will purchase shares of Security A at the price offered. If you accept a sell offer, you will sell shares of Security A at the price offered. You may also purchase shares of Security A within the market. You may also purchase shares of Security A within the market. You may also purchase shares of Security A within the market.

The market will remain open for 5 minutes during which time you can purchase or sell shares from other participants. You may trade shares from as many sellers as you wish, so long as you still have money left to do so.
Appendix 4: Market Interface and Instructions for $2.00 seller in Experiment 2 (with induced endowment effect)
References


Vita

Jessica Zinger attended Grafton Memorial Senior High School in Grafton, Massachusetts. She graduated from Bentley University in 2002 with a degree in Mathematics. For nine years she worked at EMC, holding multiple roles in the Professional Service lines of business. She earned a Master’s of Science in Operations from Worcester Polytechnic Institute in December, 2009 and a Master’s in Business Administration for Bentley University in May, 2013. In September, 2013 she entered the Bentley University Ph.D. Program.

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This manuscript was typed by the author.