

Prediction Markets To Forecast Electricity Demand*

Luciano I. de Castro[†] Peter Cramton[‡]

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Abstract

Forecasting electricity demand for future years is an essential step in resource planning. A common approach is for the system operator to predict future demand from the estimates of individual distribution companies. However, the predictions thus obtained may be of poor quality, since the reporting incentives are unclear. We propose a prediction market as a form of forecasting future demand for electricity. We describe how to implement a simple prediction market for continuous variables, using only contracts based on binary variables. We also discuss specific issues concerning the implementation of such a market.

Keywords: Forecast of electricity demand, power generation planning, implementation of prediction markets, forecast of future demand, mechanism design of capacity markets, prediction market for continuous variables, winner-takes-all contract, index contract.

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[†]Department of Economics, University of Illinois at Urbana-Champaign. E-mail: de-castro.luciano@gmail.com.

[‡]Department of Economics, University of Maryland. E-mail: pcramton@gmail.com

1 Introduction

An essential step of resource planning in electricity markets is assuring that there will be sufficient resources to meet future demand. Building capacity is costly and takes time. However, the economic consequences of an electricity shortage may be severe. Thus, when setting capacity targets the regulator must balance the cost of excess capacity against the cost of shortage. The question we address here is how can we get an accurate prediction of the future demand.

A common approach in many markets is to survey the distribution companies about their predictions of future demand. Although some markets try to provide incentives for the distribution companies to make accurate estimates, such as in Brazil, many other markets provide ambiguous incentives. As a result, distribution companies may be motivated to over or under estimate the future demand.

Even if the distribution companies have the proper incentives to make their best predictions with respect to the future demand, it is not clear that this procedure of utilizing distribution companies' predictions will produce the best possible results. The distribution companies may lack relevant information to make this prediction. Other market participants (such as large consumers and generators) also may have relevant information for forecasting the future demand. If this is the case, then relying just on the distribution companies' estimate may be problematic.

A related problem is the fact that the distribution companies are asked to give just a number as their prediction of future demand. If the correct incentives are in place, such a number would be the expectation of the future demand according to the belief of the distribution company. While this number is useful, it contains no information about the probability that the actual demand will be significantly above it. Indeed, the probability that the realization of a random variable is significantly above its expected value depends on the variance of the demand, not its expectation. This missing information (variance) is extremely important, given the high costs of a shortage of capacity. Thus it is easy to understand how even with distribution companies doing their best to report an accurate *expected value* of the demand, we still would not know the correct amount of capacity to acquire: if the variance of the future demand is high, the prediction would not be the optimal capacity because of the large asymmetry in the cost of having too little versus too much capacity. Ideally the regulator would have an estimate of the entire

probability distribution of the future demand.

Is it possible to improve upon the standard method? The purpose of this paper is to show that a simple mechanism can produce more reliable and complete information about the future demand of electricity. This mechanism is based on prediction markets.

Prediction markets are markets whose main purpose is to reveal information about the likelihood (probability) of some verifiable event. There is an increasing interest in prediction markets. As Tziralis and Tatsiopoulou (2006) report, there is an explosion of articles about such markets. The interest has arisen from the success of these markets in predicting the outcome of future events, outperforming specialists' predictions. For surveys about prediction markets, see Wolfers and Zitzewitz (2004), Tziralis and Tatsiopoulou (2006), Pennock and Sami (2007) and our section 2.

We argue that prediction markets can enhance resource planning in a straightforward way. For this, we first describe the basic mechanism of prediction markets in section 2. Since our application is of a continuous variable, section 3 reviews the literature and describes some methods for evaluating distributions of continuous variables. We then propose a new method in section 4 and argue that it has a number of advantages in comparison to other methods. Section 5 discusses some practical issues regarding the implementation of our method. While we recognize that more sophisticated mechanisms can be proposed, we argue in section 6 that the implementation of these mechanisms may face some difficulties. In section 7 we conclude.

2 Basic description of prediction markets

Prediction markets may be created with many different types of assets or contracts. See Wolfers and Zitzewitz (2004) for a description of the more common assets. Although we will also mention some of those below, our method will rely only on a simple set of assets: the “winner-takes-all” contract. A “winner-takes-all” contract is an asset that pays \$1 if a well-specified event has occurred up to some specific date and \$0 otherwise.¹

The whole idea behind prediction markets is that the price of an asset

¹We insist that there is a date and the event is well-specified to avoid problems with the verification of the contract. As an illustration of the potential problems, Ortner (1998) reports a case of a prediction market on whether a software project would be delivered to the client on schedule, but the client changed the deadline.

reflects the probability of its return, that is, the market aggregates information. Nevertheless, a debate over the property of information aggregation by prediction markets still exists. In the following subsection, we review the evidence on the good properties of prediction markets and, in the subsequent subsection we describe the theoretical debate about possible problems.

2.1 Evidence on prediction markets

The recent attention devoted to prediction markets both in academic circles and the media, including a best-selling book (Surowiecki (2004)) may suggest that the use of prediction markets is a recent phenomena. However, Rhode and Strumpf (2006) report that a market for US presidential elections has functioned on Wall Street for many years since the Civil War (1880-1944). In fact, prediction markets are essentially betting markets, and betting markets exist since primitive ages. Figlewski (1979, p. 78) observes that “betting on horse races is a custom dating back thousands of years” and adds the ironic comment that “one may wonder whether the comparatively recent development of trading in corporate equity will prove to be as durable an institution”. The fundamental characteristic of prediction markets that distinguish them from standard betting markets is the centrality of the information contained in the traded prices.²

This increasing interest for prediction markets may be explained by the overwhelming evidence suggesting that prices in prediction markets do convey valuable information, in many different settings.

In the outcome of political processes, a famous example is the Iowa Electronic Market (IEM), functioning since 1988. The IEM was first discussed by Forsythe, Nelson, Neumann, and Wright (1992), but see also Berg and Rietz (2006), Berg, Forsythe, Nelson, and Rietz (2008) and Berg, Nelson, and Rietz (2008). In particular, the IEM has been shown to (1) predict well both shortly before an event (Berg, Forsythe, Nelson, and Rietz (2008)) and through time (Berg, Nelson, and Rietz (2008)); (2) forecast better than alternative means (Berg, Nelson, and Rietz (2008)); and (3) be accurate not just on average, but on a case-by-case, contract-by-contract basis (Berg, Forsythe, Nelson, and Rietz (2008)).

²Accordingly, the evidence on betting markets spans a long time period. In general, betting markets are accurate in predicting outcomes, except in the tails, where there is a longshot bias. See Thaler and Ziemba (1988) and Sauer (1998).

Plott (2000) offers a number of results illustrating the remarkable informational capabilities of (prediction) markets. Chen and Plott (2002) describe how a prediction market organized by Hewlett-Packard Corporation for the purpose of making sales forecasts performed better than traditional methods. Figlewski (1979) finds that horse race markets beat horse race experts in their predictions. Pennock, Lawrence, Giles, and Nielsen (2001) report that Oscar markets provide better predictions than columnist forecasts in the Hollywood Stock Exchange.

Maloney and Mulherin (2003) describe a prediction market surrounding the crash of the space shuttle Challenger. They show that while the panel of specialists took several months to determine which of the mechanical components failed during the launch, the market was able to single out the firm that manufactured the faulty component very quickly after the event.

Arguably, prediction market forecasts are often more accurate and less expensive than those obtained with other more traditional forecasting methods, such as expert opinions or pools (see e.g. Berg and Rietz (2006)). Also, prediction markets rapidly incorporate new information. See Berg and Rietz (2006) for an account of the “1996 Colin Powell Nomination market” in the IEM.

According to Hanson (2006b), “so far, speculative markets have done well in every known head-to-head field comparison with other forecasting institutions”. Wolfers and Zitzewitz (2004) and Hahn and Tetlock (2006) report other examples of success of prediction markets and suggest applications. The site <http://www.ideosphere.com> offers another illustration of the use of prediction markets. It maintains prediction markets for many socially and scientifically relevant questions, some of which have closing dates as far as 2100!

2.2 Other topics related to prediction markets

The implementation of a prediction market for future electricity demand, as we suggest in this paper, requires dealing with a number of issues that go beyond the accuracy of these markets. We discuss below some political aspects of implementing a decision market, the justification of seeing prices as probabilities and the possibility of manipulation.

Decision markets and public reaction

From the success of prediction markets, Hanson (1999) was one of the first to propose the use of such markets for making decisions. He proposed “decision markets” created specially for the purpose of evaluating various policy alternatives. Berg and Rietz (2003) advance this idea with a description of how to implement “conditional prediction markets”.

An attempt of real implementation of a decision market in the public domain was a proposal of a prediction market in terrorism futures, the “Policy Analysis Market (PAM).” Hanson (2006a), who was personally involved, presents a detailed report of the implementation of the project and how it came to an end. His account suggests that the main problem was misunderstanding, promoted specially by some politicians and the media. He also suggests that the attack was managed “in order to embarrass the Bush administration via its association with the freshly vilified John Poindexter, and by tainting it as being a bit too mad about markets” (p.261). Among the main concerns were the possibility of manipulation of the markets by terrorists, who could find a profitable reward for their activities; and the “terror” that the market itself could create in the public. After the very negative impact in the media, the project was quickly abandoned.

Fortunately, the application suggested here is about an *economic* phenomena (electricity demand) and not a politically controversial topic as terrorism. This fact can help to avoid the main problems involved in the actual implementation of the market. However, in countries where market oriented proposals are negatively seen and can, therefore, be politically explored, some precautions should be taken and a “communication plan” seems desirable. See a discussion in section 5.

Prices as probabilities

Although there is strong empirical and experimental evidence that predictions markets do work, the theoretical analysis of these markets seems much less developed. Apparently, we still do not have a good theory to explain *why* such markets perform so well. Although Berg and Rietz (2006) forcefully argue in favor of prediction markets, they concede that theoretical explanations are limited and quote Vernon Smith, who wrote: “Things sometimes work better than we had a right to expect from our abstract interpretations of theory” (Smith (1998)).

A few papers address this theoretical question. Manski (2006) shows in a competitive simple model with investment constraints that prices *should*

not be interpreted as probabilities. Trying to offer a theoretical justification, Wolfers and Zitzewitz (2006b) find that the equilibrium price of an Arrow-Debreu security written on an event E is given by the mean or a certain quantile of the distribution of beliefs among traders about the probability of E . Ottaviani and Sorensen (2008) assume that market participants have heterogenous beliefs and consider a rational expectations equilibrium. They show that prices under-react to the arrival of new information.

Manipulation

The possibility of manipulation is a real and important concern. If some participants are sufficiently big and have special interests in the outcome of the market, then they may act to undermine the performance of the prediction market. This is a important problem that is still not completely understood. For example, Wolfers and Zitzewitz (2006a) placed this problem in their list of five open questions regarding prediction markets, but report that known attempts to manipulate public prediction markets have largely failed.

There are two main forms of manipulation: outcome manipulation and price manipulation. Outcome manipulation refers to the case where the actions of market participants may affect the likelihood of the event. For example, suppose that the event is the timely completion of a corporate project and the market participants involve people working on the project. Then the pessimists who have bet on delay can make less effort to the complete the project, while the optimists may do the opposite. Outcome manipulation has been discussed by Hanson (2006b), Wolfers and Zitzewitz (2006a) and Ottaviani and Sorensen (2007). Lieli and Nieto-Barthaburu (2009) discuss the slightly different “feedback problem”. They explore the consequences of the idea that forecasts produced by prediction markets might be used in subsequent decisions that influence the likelihood of the event. For instance, if the prediction market indicates a high likelihood of an epidemic flu, then the government can take preventive measures to reduce this danger. The “feedback problem” occurs exactly when decisions can have an impact on the very event the market was meant to forecast.

For our purposes, the more important topic is price manipulation, which may occur when traders have an interest in affecting the market price because they want to affect decisions based on that price. Hanson and Oprea (2004) work with Kyle (1985)’s model of speculative trade and show that the manipulator’s mean target has no effect on the market price. However, the

presence of manipulators increases the expected rewards of informed traders and thus, indirectly contributes to market accuracy. On the other hand, Goldstein and Guembel (2008) offer a model where manipulation not only can exist, but also it can have non-trivial impact on market efficiency.

In the empirical framework, Rhode and Strumpf (2006) (see also Rhode and Strumpf (2004)) considered attempts of (price) manipulation in three markets: presidential elections on Wall Street (1880-1944), Iowa Electronic Market (1988-present) and TradeSports (2001-present). They found that manipulative attempts are able to change the prices of contracts during a short period of time (typically less than one hour), but the prices eventually return to their levels previous to the manipulative attempts. We found only one report of successful manipulation in a prediction market for an election in Berlin, in 1999. See Hansen, Schmidt, and Strobel (2004).

Manipulation was also investigated using experiments by Camerer (1998), Hanson, Oprea, and Porter (2006) and Veiga and Vorsatz (2009). In Camerer (1998)'s experiment, \$500 and \$1,000 bets were made at horse race betting markets, and canceled shortly thereafter. The bets caused a transient change in the odds, but the net effect was close to zero and statistically insignificant. In a laboratory experiment, Hanson, Oprea, and Porter (2006) conclude that manipulators were unable to distort price accuracy, since participants without manipulation incentives compensate for the bias introduced by manipulators. Veiga and Vorsatz (2009) reports that manipulation can occur if the true value of the asset is low, but in general it does not occur when this value is high.

This review shows that although manipulation was detected in some cases, it typically has no significant impact. However, since the decisions to be made from an electricity demand prediction market can involve huge sums, it is possible that the economic incentives for manipulation will be high enough to undermine the accuracy of the market. Because of that, in section 5 we suggest some precautions that could help to avoid this problem.

2.3 Framework for this paper

Throughout the paper we will assume that the price of an event-asset in a prediction market reflects the probability of that event, given the aggregated information of market participants. It is useful to state this assumption formally. For this, we will need some notation.

Let E be a well specified event and let $\Pr(E)$ denote the best possible

probability prediction for the occurrence E , that is, the probability that perfectly aggregates all the information possessed by market participants. Also, let p_E denote the market price of the winner-takes-all asset based in the event E . If the event is clear from the context, we will write p instead of p_E .

Assumption 1 (Information aggregation) *For any well specified event E , $p_E = \Pr(E)$.*

From Assumption 1, we will refer to p interchangeably as the market prediction price and as the probability that the event occurs. Assumption 1 is a basic working assumption for all applications of prediction markets. If it does not hold, the foundations of prediction markets are undermined. We stress, however, that this is an *assumption*: it is not true in all possible markets and a prediction market designer must verify that it is at least approximately true.

3 Prediction markets with continuous variables

Some uncertain outcomes are clearly binary in their nature, such as the event that the Republican candidate wins the American election. However, many others are continuous random variables. For instance, how many units a new product will sell, the percentage of electoral vote by some candidate, or the electricity demand at a future time. At first sight, it is not obvious how to use markets with only winner-takes-all assets in order to obtain information about the probability distribution of these variables.

Hanson (2003) proposes market scoring rules, which combines ideas of scoring rules and the standard design of prediction markets.³ At each time t , there is a *current* probability distribution p^t and a market participant reports some probability r^t that she thinks is the most correct one and this will lead to the probability for the next period, p^{t+1} . This is associated through some scoring function to a cost (or gain) associated to the change of probabilities. The final payoff of the market participants will be the sum of gains and

³Hanson (2003) is not restricted to continuous variables. In fact, he address more the case of binary variables. However, since he can treat any combination of a number of binary variables, the continuous case can be approximated discretely.

losses along the trades in the different periods. Many scoring rules can be adopted, but quadratic and logarithmic scoring rules are the more common. See Hanson (2003) for more details.

It is possible to obtain the expectation of a continuous random variable using the index contracts, as Wolfers and Zitzewitz (2004) call them. Index contracts pay \$1 for each unit of the outcome that is realized. For example, if the units are percentage points of popular vote for the Democratic candidate, then the contract will pay \$44 if the Democratic candidate obtained 44% of the popular vote. The idea behind this kind of contracts is that if $E[X]$ denotes the expectation of (the units of) X according to the best possible probability, then $p = E[X]$.

Of course this idea is in the same spirit of Assumption 1, since $E[X] = \Pr(\{X = 1\})$ for a binary variable. However, Assumption 1 *does not* imply that the price p of the index contract is equal to $E[X]$. The reason is that this assumption refers only to events or binary variables. Of course we could require Assumption 1 to hold also for continuous variables but, as we stressed before, Assumption 1 is not free of controversy. Despite the justifications for that assumption, its conclusion is less tested for continuous (index) contracts than it is for binary (winner-takes-all) contracts. Perhaps there is no gap between the properties of winner-takes-all and index contracts prediction markets, but it is better to be conservative in this matter and work with the weakest conditions that can deliver the desired result.

Also, note that this approach only gives information about the *expectation* of X . As mentioned in the introduction, we often are interested in obtaining more information about the distribution of X . For addressing this problem, Wolfers and Zitzewitz (2004) propose the use of contracts that pay x^2 dollars if the outcome of X is x . In this way, the price of the contract will be $E[x^2]$ and from this and $E[X]$, one can obtain the standard deviation $\sigma_X = \sqrt{E[x^2] - (E[x])^2}$ of X . They conclude that “adding even more complicated index contracts can yield insight into higher-order moments of the distribution” (p. 110).

Yet another method to make evaluations of continuous variables with prediction markets is the one used by Chen and Plott (2002) in the evaluation of future sales of a new product developed by HP. They divided “the real line into about 10 or so (exact number depends on the event) intervals”. If the final outcome fell in an interval, the corresponding security would pay \$1 per share at the end. Note that each asset is an winner-takes-all (binary) asset. Therefore, Assumption 1 applies. Chen and Plott (2002) report strong

results in the HP experiment using this implementation.

The described implementation was successful, but it has at least a potential limitation for other cases. If one is interested in more accuracy in the outcome, then the only way to achieve this accuracy is to increase the number of intervals. However, if there is a large number of intervals, then the problem of *thin markets* becomes important: there is not enough trade in each asset to make the information reliable. Another problem, which actually happened in Chen and Plott (2002)'s experiment, is that the sum of prices (that is, probabilities, from our assumption) may not equal 1. Of course this may be attributable to the lack of expertise or the lack of enough trade in the markets. However, the occurrence of this fact clearly undermines the argument for Assumption 1 and raises some doubts about the approach.

As we will show in the next section, our solution avoids all these problems and yet remains simple.

4 Cumulative Distribution Function Prediction Market

In this section, we describe a simple method of implementing a prediction market for continuous variables using only winner-takes-all (binary) assets. In order to do so, let us take the values $x_1 < x_2 < \dots < x_n$ in the set of possible values of the variable X . Now, for $k = 1, \dots, n$, define the event $E_k \equiv [X \leq x_k]$, that is, E_k is the event that the realization of X is not greater than x_k . The cumulative distribution function (c.d.f.) market that we propose is simply a prediction market with n winner-takes-all contracts based in the events E_k , for $k = 1, \dots, n$. The following analysis justifies this name:

Let p_k be the price of the asset k , that pays \$1 if E_k occurs and nothing otherwise. Then, by Assumption 1 we have:

$$p_k = \Pr\{E_k \text{ occurs}\} = \Pr[X \leq x_k] = F_X(x_k),$$

where F_X denotes the cumulative distribution function (c.d.f.) of X .

Note that a simple arbitrage argument guarantees that $p_k \leq p_{k+1}$ for all $k = 1, \dots, n-1$. Indeed, if $p_k > p_{k+1}$, a trader can guarantee making money by buying asset $k+1$ and selling asset k . Therefore the points in the c.d.f. F_X produced by the market will be monotonic. Also, note that it is not

necessary that $F_X(x_n) = 1$, since the event $[X > x_n]$ can have a positive probability.

Let us compare this procedure with the procedures previously described. First, while index contracts yield information only about the expectation of X , the above procedure will provide much more information. By adding additional points, we can get finer information about the distribution of X . Since this procedure gives a good approximation of the whole c.d.f., we can calculate all moments we need.

Note that we can create new contracts even after the market is initiated. In fact, this ability to create new contracts may even be desirable. Let us suppose that there is an important jump in the prices of the contracts k to $k + 1$. This indicates that there is a large probability of X being between x_k and x_{k+1} . Since we may not know this before the experiment, this problem could not be anticipated. This large probability indicates that we may be interested in knowing the distribution between x_k and x_{k+1} with more detail. To obtain this information, we just need to choose a value v between x_k and x_{k+1} and create a new asset for the event $[X \leq v]$. The monotonicity property described above then implies that the price of the new asset will be between p_k and p_{k+1} . Note that nothing changes for the other contracts.

Note also that since prices of new contracts already come restricted to some intervals, the *thin markets* problem is reduced. Even if there is absolutely no trade in the asset k , we know that its price *is* between p_{k-1} and p_{k+1} . So, we can have a large number of contracts, with small trade in each of them, but the market still works sufficiently well—provided that there is sufficient trade overall.

These advantages also make clear why this method is better than the evaluation of frequencies used by Chen and Plott (2002). Not only does the creation of new intervals become problematic with the frequency approach, but the *thin markets* problem may also be severe. As we discussed, our approach avoids these problems.

5 Implementation of prediction markets for future demand of electricity

Using the method described in the previous section, it is easy to design prediction markets for the future demand of electricity. It is necessary to

begin by defining how the future demand will be measured and verified. (The demand may be expressed in MWh or in percentage increments with respect to the current demand.) The geographic area and the interval of time for which the future demand is considered are also important. Once these specifications are made, the market designer has to choose values $x_1 < \dots < x_n$ that cover the likely values of the demand X . From this, the method described in the previous section naturally applies. Note that the market designer has the freedom to create new contracts after the beginning of the actual implementation of the market, as we also discussed in the previous section.

Of course, there are a number of details that have to be clarified. One of them is who can participate and what is the maximum amount traded by each market participant (if any). Many prediction markets have included limits in the participation, probably to avoid manipulation and excessive risk taking by some individuals. However, low limits may reduce the liquidity of the prediction market, undermining its function. The literature has not provided guidance so far in the proper way to evaluate this trade-off. Below, we discuss other issues that must be considered in the actual implementation of the idea proposed in this paper.

Manipulation

An essential aspect for price manipulation, as we discussed in section 2, is the incentive to try to manipulate the market. In the electricity demand prediction market, this could come as profits for over investment in capacity (but also for under investment). Constructors may profit from over investment, while existing generators may profit from the high electricity prices that under investment may cause. Fortunately, these two incentives go in opposite direction.

It is prudent, however, to create safeguards to mitigate manipulation. For this, we suggest the following:

- consider the price signal of the prediction market as indicative, not as mandatory. In other words, the authority responsible for deciding how much capacity to construct is not constrained to select the capacity indicated by the prediction market;
- maintain the current, standard way of predicting future demand and compare it with the outcomes of the prediction market;

- monitor the market for attempts of manipulation, and establish punishments for manipulative behavior.

From this, possible manipulators will have to weigh their possible profits from manipulation with: (1) the possibility that the manipulation is ineffective because the energy authority addresses it; (2) the possibility of punishment; (3) the possibility that a manipulation will produce no result from the market mechanism itself; and (4) the likely losses in the prediction market that the attempts of manipulation will imply. With all these conditions, manipulation may well be unattractive.

Also, even the point that it is not mandatory does not go against the basic idea of a prediction market. Most commonly, the purpose of the market is to provide information, not to directly make decisions. The decision will be made by the appropriate decision maker, using all the information available (including the indications of manipulation that would reduce the information value of the price itself).

Communication of the prediction market project

As the “terrorism futures” case illustrates (see Hanson (2006a)), the communication of the project to the public can be an essential element to its successful implementation. It seems essential to develop a “communication plan” as a part of the implementation effort. This plan would not only specify what ideas should be emphasized to the public (accuracy, low cost of the predictions, energy security, etc.), try to anticipate potential reactions, and prepare the correspondent clarifications, but also devise a system to make all potentially interested market participants aware of its rules and conditions. The communication to the energy industry participants is important because they may be directly affected by the market outcomes and may also have stronger incentives to participate. Also, it seems prudent to open public hearings about the project before actually implementing it.

Elasticity of the demand

Another issue that should be addressed in an implementation is the dependence of the demand with the price. Although the demand for electricity is inelastic in the short-run, resource planning and capacity markets may operate five or more years in advance and, with this time interval, the demand can be more elastic. For example, plants that require large electricity inputs, such as aluminum smelters, may not be constructed depending on the future

price of electricity. Thus, it is desirable that the prediction market allows for the dependence of the demand with the price. This objective can be achieved using conditional contracts, such as those proposed by Hanson (1999) and Berg and Rietz (2003). We adapt their idea for future demand of electricity as follows.

Let P_1, \dots, P_m be a set of events covering all relevant prices. These sets can form a partition of all conceivable prices, but this is not necessary. In particular, P_j can be the event that the price of electricity will be between y_j and \bar{y}_j or, alternatively, that the price of electricity is below (or above) y_j . In any case, let E_k be the event that the demand is below x_k , as described in the last section. Then, let us consider a market with winner-takes-all contracts based on the events P_j (whose price will be denoted p_j) and $E_k \cap P_j$ (whose price will be denoted p_{kj}), for all $j = 1, \dots, m$ and $k = 1, \dots, n$. Then, Assumption 1 implies that the conditional c.d.f.

$$F(x_k|P_j) = \Pr(E_k|P_j) = \frac{\Pr(E_k \cap P_j)}{\Pr(P_j)}$$

is given by p_{kj}/p_j . This gives the c.d.f. of the demand of electricity conditional to electricity prices being on P_j , as we wished to obtain.⁴

Other issues

There are still other issues that need to be properly addressed in an actual implementation: duration of the contract and how to make its value persistent in time (maybe just inflation-free or with some small interest); how to ensure payments at the end of the contract; the custody mechanism; the amount of subsidy, if any;⁵ limits for participation per individual of firm; and the mechanisms for monitoring activity (for detecting attempts of manipulation), without constraining truthful bets. Although the resolution of all these issues are important, the best implementation likely varies from case to case. Therefore, we refrain to add more here.

⁴Note that this implementation also gives a forecast for future prices of electricity, which can be useful for market participants for independent reasons (recall the example of investment on an aluminum smelter mentioned above).

⁵Experience has shown that prediction markets are in general inexpensive to operate. Some authors advocate for the use of subsidies for promoting participation, but this may be unnecessary.

6 More sophisticated mechanism designs

Although we have considered prediction markets only to give information about future demand, of course it is possible to conceive more sophisticated mechanisms in which the demand may have a more active role.

In this way, the prediction of the future demand can enter directly the market for future capacity. For this, we must have double auctions, that is, auctions in which both demanders and suppliers have active participation.

There are, however, some practical problems in pursuing this idea. First, there may be resistance from distribution companies not used to having an active role in capacity markets. Second, it is not clear how susceptible to manipulation such a market would be. Third, political pressure and lack of confidence in the performance of an (unknown) market may make the actual implementation difficult.

Although we are not pessimistic about the design of more sophisticated capacity markets, the above reasons suggest that to propose a satisfactory theoretical design and to bring this proposal from theory to practice may require considerable efforts.

7 Concluding remarks

This paper proposes the use of prediction markets to inform the regulatory bodies that are responsible for resource adequacy. The proposed method is simple and easy to implement. Moreover, it provides much more information than the current practice of only asking distribution companies to report their predictions for future demand. Simply asking for estimates allows easy manipulation—the distribution companies may have incentives to overstate or understate the demand—the proposed prediction market is less susceptible to manipulation.

Improved prediction enables the regulator to better manage the costs of either too little or too much capacity.

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