PREDICTING CRIME

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Prediction markets have been proposed for a variety of public policy purposes, but no one has considered their application in perhaps the most obvious policy area: crime. This Article proposes and examines the use of prediction markets to forecast crime rates and the potential impact on crime policy, such as changes in resource allocation, policing strategies, sentencing, post-conviction treatment, and so on.

First, we argue that prediction markets are especially useful in crime rate forecasting and criminal policy analysis because information relevant to decisionmakers is voluminous, dispersed, and difficult to process efficiently. After surveying the current forecasting practices and techniques, we examine the use of standard prediction markets—such as those being used to predict everything from the weather to political elections to flu outbreaks—as a method of forecasting crime rates of various kinds.

Second, we introduce some theoretical improvements to existing prediction markets that are designed to address specific issues that arise in crime rate forecasting. Specifically, we develop the idea of prediction market event studies that could test the influence of real and hypothetical policy changes on crime rates. Given the high costs of changing policies, such as issuing a moratorium on the death penalty or lowering mandatory minimum sentences for certain crimes, these markets provide a useful tool for policymakers operating under uncertainty.

But, the event studies and the other policy markets we propose face a big hurdle because predictions about the future imbed assumptions about the very policy choices they are designed to measure. We offer a method by which policymakers can interpret market forecasts in a way that isolates or unpacks underlying crime factors from expected policy responses, even when the responses are dependent on the crime factors.

Finally, we discuss some practical issues about designing these markets, such as how to ensure liquidity, how to structure contracts, and the optimal market scope. We conclude with a modest proposal for experimenting with markets in this policy area.

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INTRODUCTION

Science fiction author Philip K. Dick proposed that in fifty years or so our society will have the ability to predict certain crimes before they happen.[1] Policymakers today, however, do not have certain knowledge of future events—like what the crime rate will be in Chicago in the next hour, next year, or next decade—so they have to resort to less precise forecasting tools. These tools include using gut feeling, examining what has been done in the past, and modeling based on maps overlaid with things like past crimes, the location of liquor stores or demographic data. Policymakers extrapolate from past events, as they must, but do so in a manner that is not systematic, transparent, or likely to lead to the best available forecast. Based on a review of the extant literature and discussions with various officials at all jurisdiction levels across the country, it is highly doubtful that any serious, systematic forecasting of crime rates is done anywhere. It is safe to say that the current approach to forecasting crime, insofar as it exists, is extremely crude.[2] This is deeply puzzling. Public safety is the most important metric for elected officials (especially at the local level) and allocating scarce crime-fighting resources efficiently is an essential element of achieving public safety. There are several possible reasons for this failure.

First, existing tools may simply be insufficient to provide meaningful forecasts. Technical forecasting, using economics models, computer technology, and mapping tools, is a modern phenomenon,[3] and these methods are unproven, difficult to interpret, and expensive to set up and operate, especially for communities with tight budgets. Although New York City and some other large cities have deployed mapping programs and management tools designed to improve resource allocation and planning, these are by and large backward looking, rarely theoretically sound, and subject to the biases and idiosyncratic tendencies of the few individuals who operate them.

No police department or other law enforcement agency has, to our knowledge, deployed any of the emergent forecasting models being developed by academic criminologists. Since cost is not likely a barrier in these cases as most of the software and ideas are free,[4] it is possible to conclude that these methods are too crude, too complex, or too unreliable to be valuable. In other words, the costs of implementation currently exceed the expected benefits, which actually may be so low that even if the total cost of deployment were near zero, the tools would add little or no value.

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1. *See* PHILIP K. DICK, THE MINORITY REPORT (2002). The short story was made into a popular 2002 movie directed by Steven Spielberg. MINORITY REPORT (Twentieth Century–Fox Film Corp. 2002).

2. For example, mapping crimes by police precinct or beat and then assigning more resources to the areas with the most hits in the past.

3. The first known academic paper on crime forecasting is Andreas M. Olligschlaeger, *Artificial Neural Networks and Crime Mapping*, *in* CRIME MAPPING & CRIME PREVENTION 313 (David Weisburd & Tom McEwen eds., 1998).

4. For example, FacilityCop, a software-forecasting tool developed at Temple University, is available as a free download. *See* Facility Cop Software, Temple Univ. Dep't of Criminal Justice, http://www.temple.edu/cj/faccop/ (last visited Jan. 31, 2010).

A second and related reason why technical and systematic forecasting appears to be rarely used may be because it takes place in an informal, tradition-based manner inside the minds of key decisionmakers. The practice of forecasting is as old as crime regulation and policing, since all policymakers (from the governor to local police chiefs) must make decisions about how to allocate scarce resources.[5] In the absence of specific forecasting tools, the most likely methods of predicting crime are human-based pattern recognition and the gut instincts of decisionmakers. In other words, police chiefs have a feeling about where crimes will occur, or the governor has an idea about crime patterns or the impact of tools like the death penalty or parole, and these officials use these feelings and ideas to make policy decisions.

This kind of decision-making may be successful in some instances, given that the decisionmakers have experience, and given that it entails some ex post political accountability checks. On the other hand, these techniques will undoubtedly be crude, subject to political biases, and possibly systematically skewed by decision-making heuristics and errors to which well-meaning decisionmakers are invariably subject. Forecasts may also be distorted in cases where the private value of a particular decision exceeds its social value.[6] Although this type of forecasting should not be quickly discarded,[7] we show an alternative to (or more likely a complement to) gut-based decisions that will not only improve current forecasts, as well as accountability and transparency, but will also expand opportunities for policymakers to "experiment" with policy changes.

A final reason for the lack of systematic forecasting may have to do with something we might call "politics" or "public choice." There are many possible explanations that fit under this rubric: it may be politically difficult to justify (to colleagues, constituents, or subordinates) an investment in forecasting over, for instance, another cop on the beat; police unions or police management may resist changes that are socially efficient but have high private costs for them; certain political constituencies might not want crime predictions, especially for certain areas of a city or state, to be publicly available in such a conspicuous form; decisionmakers also might not want information on crime in particular neighborhoods to be forecast, since this might scare off developers or new residents and might discourage current residents by revealing that current policies

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5. This includes: the number of prosecutors, the amount of jail space, the number and type of vehicles deployed, the number of cops on the beat, the kind of detection technologies deployed, and so forth.

6. These barriers to effective decision-making, extracted largely from work in psychology, sociology, and economics, are described in detail in the legal literature. *See, e.g.*, BEHAVIORAL LAW & ECONOMICS (Cass R. Sunstein ed., 2000) (identifying numerous mental and psychological heuristics that limit human abilities to reason rationally).

7. One is reminded of the "Moneyball" phenomenon, where baseball executive Billy Beane showed how new, formal methods of data analysis can radically change the conventional wisdom about how to solve a particular problem—in Beane's case, how to evaluate inchoate talent in prospective big leaguers. *See* MICHAEL LEWIS, MONEYBALL: THE ART OF WINNING AN UNFAIR GAME (2003). We believe our proposal has the ability to change long-standing practices in the same way that Beane's application of Sabremetrics did for baseball.

are failing despite (or because of) city efforts; the whole concept of betting on crime might be normatively troubling to some citizens.

Given these possible reasons for the apparent lack of systematic crime forecasting, this Article contributes a new forecasting tool—crime-forecasting prediction markets—that may be more affordable, accessible, and accurate for decisionmakers. We propose two general types of markets: the first are simple crime rate prediction markets that are similar to those being used currently to predict everything from the weather to political elections to flu outbreaks; the second are various contingent markets or prediction market event studies that can be used to inform policy decisions on subjects like sentencing, the death penalty, the use of surveillance technology, and so on.

This Article argues that these markets could be used to forecast crime and inform crime policy in a vastly more reliable and informative manner than current practices. Instead of decisionmakers relying on certain individuals, a certain model, a certain theory, or certain information, they can rely on a market-based aggregation of available information. This is especially the case in light of several technical innovations we contribute that (1) allow policymakers to interpret market prices even when the prices include imbedded predictions about future policy changes and (2) allow policymakers to estimate the causal impact of hypothetical policy changes on crime rates.

Part I of the Article describes the basic theoretical underpinnings of prediction markets. These markets are fairly well understood, but we provide some additional thoughts of particular relevance to crime prediction markets. We also introduce the current methods for forecasting crime, along with their limitations. In Part II, we make two contributions to the prediction markets and crime forecasting literature. First, we describe how prediction markets can be tailored to address specific policy issues that require improved methods of predicting the future, using crime policy as an example. Second, we introduce some theoretical improvements to existing prediction markets that are designed to address specific issues that arise in policy-making applications. Specifically, we offer a method by which policymakers can interpret market forecasts in a way that isolates or unpacks underlying crime factors from expected policy responses, even when the responses are dependent on the crime factors. Using this mechanism, it may be possible to decentralize crime policy in the same way that monetary policy has been transformed by the introduction of forward markets for interest rates, inflation, and other macroeconomic indicators.

We also develop the idea of prediction market event studies that can be used to test the influence of policy changes, both real and hypothetical, on crime rates. It is this latter possibility that unlocks the true power of prediction markets, as we show a way in which policymakers can get broad-based estimates of changes to public safety enforcement *before* they are implemented. Given the life and death implications that may arise from changes in policy, as well as the high cost of making changes in resource allocation, public safety is an area that may be plagued by insufficient experimentation. The models we offer are a way around this problem.

We then discuss some design issues and objections in Part III. Part IV concludes with a modest proposal and some open questions.

I. FORECASTING & PREDICTION MARKETS

A. The Forecasting Problem and How Prediction Markets Can Solve It

The challenges involved in predicting crime rates or the impact of different crime policies are very similar to those in other forecasting domains. Classic examples include predicting sales of a product, changes in interest rates, the likelihood of a terrorist attack, or the outcome of political elections. In each of these cases, the inputs needed to generate a reliable forecast may be skewed by a variety of factors, some of which might be benign but disruptive, and some of which may be selfish and opportunistic.[8] For example, relevant information may be quite dispersed; true experts may be difficult to discern from over-confident charlatans; a wide variety of alternative models may exist, but no obvious "best" model may prevail; political or social concerns may lead some to misrepresent their information; decision-making heuristics and barriers to information may inhibit analysis by key decisionmakers; and there may be few incentives for uncovering new information and developing or identifying improved models. Given the similarities in the forecasting problems across these varied areas, it is not surprising that a recent forecasting innovation—prediction markets—has been used in each of these cases.[9]

As detailed sufficiently elsewhere, prediction markets are simply futures markets where the payoffs of the contracts traded are tied to a future event, such as how many printers will be sold in the next quarter, who will win the next presidential election, or the number of homicides committed in Chicago in the next year.[10] By constructing these futures contracts in a transparent manner, researchers can interpret the price of contracts as a market-aggregated forecast. For instance, if a contract that pays $1 if next year's burglary rate is higher than last year's is currently trading at $0.95, then the market is suggesting that it is extremely likely (about 95% likely) that the number of burglaries will rise. If an array of

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8. Benign but disruptive factors include various decision-making heuristics that limit the ability of individuals to make good decisions. For example, the evidence suggests that individuals overestimate the likelihood of events that have occurred recently or to them. This is known as the familiarity bias. Selfish and opportunistic factors are where individuals use forecasts not as a prediction mechanism, but to serve a personal interest. Sabotage is the most obvious example, whereby an individual would predict, say a drop in the price of a contract, and then act to make the price drop. The sabotage problem in the context of prediction markets is discussed in the literature. *See* Michael Abramowicz & M. Todd Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. 1343, 1384–85 (2007) (concluding that concerns are overblown). Additionally, we cover it briefly in Part IV below.

9. *See generally* Abramowicz & Henderson, *supra* note 8, at 1349–50 (describing markets at Hewlett-Packard used to more accurately predict printer sales than existing methods); Justin Wolfers & Eric Zitzewitz, *Prediction Markets*, 18 J. ECON. PERSP. 107 (2004) (describing existing prediction markets and their general application).

10. *See, e.g.*, Abramowicz & Henderson, *supra* note 8, at 1349–50; Wolfers & Zitzewitz, *supra* note 9, at 110.

criminologists, police chiefs, statisticians, and the general public all trade in such a market, then the price will come to reflect an aggregation of the various information sets and models used by each of these traders, leading the market-based forecast to reflect "the wisdom of crowds."[11] If the market is fairly efficient,[12] we can be fairly certain that there is no one with much better information about the future event; otherwise, they would have the incentive (be it financial, reputational, or otherwise) to trade on the information, which would then change the price or forecast.[13]

Of course, there are many reasons to be concerned that prediction markets, like all markets, are not perfectly efficient.[14] As such, the usefulness of prediction markets for crime rate forecasting (or any other forecasting purpose) is an unresolved empirical question. Nevertheless, the policy-relevant question is not whether prediction markets are accurate predictors of crime rates, but whether prediction markets yield more accurate crime rate forecasts than alternative approaches. To our knowledge crime-forecasting prediction markets have never been run, but there is a large amount of data on the relative accuracy of prediction markets compared with econometric models, experts, polls, and averages of forecasters. As Robin Hanson summarizes the evidence, these markets do very well:

> So far, speculative markets have done well in every known head-to-head field comparison with other forecasting institutions.

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11. *See* JAMES SUROWIECKI, THE WISDOM OF CROWDS (2004) (showing that in many cases, the average guess of relatively uninformed lay persons outperforms expert estimates); *see also* CASS R. SUNSTEIN, INFOTOPIA: HOW MANY MINDS PRODUCE KNOWLEDGE (2006).

12. The theoretical insight of prediction markets is simple: the price mechanism, that is, prices revealed through voluntary and competitive market-based exchanges, is the best available means for aggregating private and public information. *See* F.A. Hayek, *The Use of Knowledge in Society*, 35 AM. ECON. REV. 519, 526 (1945). As a theoretical matter, Hayek introduced this concept in his criticism of central planning, but its intellectual origins go back to Adam Smith and further, and surely its practical application is nearly as old as human society. *See* F.A. HAYEK, THE ROAD TO SERFDOM (1945). In his famous work, Hayek showed that no central authority, be it the Soviet Gosplan or the Chicago Police Department, can aggregate and process all of the information relevant to deciding how to solve a complex issue, like how much bread or how many police officers are needed in a city at a particular time and location. The economists' enthusiasm for markets is premised, in part, on the efficient markets hypothesis: in efficient markets, the price will reflect the best available guess as to value. In the context of forecasting, in a truly efficient prediction market, the market price will be the best predictor of the event, and no combination of alternative prediction models or data on criminal, demographic, economic, or other trends, can be used to improve on the market-generated forecasts.

13. For example, using the example above, if one was supremely confident that the burglary rate was going to be *lower* next year, seeing the market price of $0.95 for contracts paying $1 if the rate was higher, one would sell "short" these contracts at $0.95, expecting them to fall in price so as to profit by the drop.

14. Markets can be imperfect owing to insufficient liquidity, manipulation, inadequate or excessive regulation, poor design, behavioral heuristics of participants, and so on. These problems are as true, but no more true, for prediction markets as for other markets.

> Orange Juice futures improve on National Weather Service forecasts, horse race markets beat horse race experts, Oscar markets beat columnist forecasts, gas-demand markets beat gas-demand experts, stock markets beat the official NASA panel at fingering the guilty company in the Challenger accident, election markets beat national opinion polls, and corporate sales markets beat official corporate forecasts.[15]

Cass Sunstein's recent book, *Infotopia*, and a series of academic articles by Sunstein and others detail at length the theoretical and practical reasons for these results.[16] One reason is described by the Condercet Jury Theorem, which shows that, given certain reasonable assumptions, the probability of reaching the correct result dramatically increases as the number of individuals participating in a decision increases.[17]

Prediction markets allow any and all voices to be heard, which under the Condercet Jury Theorem should induce a movement toward better forecast estimates. In addition, Sunstein shows that in the absence of market mechanisms: mental heuristics inhibit information flow to decisionmakers; point estimates by experts or decision-making groups are less reliable than the smoothed aggregations of everyone's opinion; and even the most well-designed and well-informed groups of experts cannot in general match the power of market-based information aggregators.

Prediction markets work because they address several key factors relevant to accurate forecasting. First, they aggregate information from any and all persons holding valuable information, regardless of their identity, their social status, their position in a decision-making hierarchy, or the basis for their information. The anonymity of trades permits all voices to be heard with less cost for the speakers or providers of information. This can be thought of as the debiasing of information hierarchies. Debiasing allows those who might be marginalized to contribute, but also maintains the ability of those who rightfully hold privileged positions in the hierarchy (say because of good access to information or a history of good predictions) to have a greater say. Markets can accomplish this dual role by allowing anyone to participate anonymously (thus avoiding social hierarchies from limiting information flow) and by simulatenously rewarding individuals based on the size and correctness of their bets (thus allowing individuals with superior information to earn better returns.)

Information debiasing might be especially important in crime policy, since many believe that a major impediment to the flow of information to police and other decisionmakers is the high personal cost of disclosing information about criminal activity.[18] Moreover, those with the most valuable information about crime patterns—cops walking the beat, criminals, and citizens sitting on their front

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15. Robin Hanson, *Foul Play in Information Markets*, *in* INFORMATION MARKETS: A NEW WAY OF MAKING DECISIONS 126 (Robert W. Hahn & Paul C. Tetlock eds., 2006).

16. SUNSTEIN, *supra* note 11, at 117.

17. *See id.* at 35–36.

18. CLAYTON JAMES MOSHER ET AL., THE MISMEASURE OF CRIME 23 n.26 (2002).

porch—are those whose information and opinions are least likely to be heard in the decision hierarchy.[19] In addition, the existence of multiple public safety agencies in any jurisdiction complicates information flow in a way that increases the likelihood of error.[20]

The second reason that prediction markets work is that they provide a financial incentive to disclose information. Academics, neighbors, and public safety officials may all have relevant information but may not have the incentive to reveal it to officials because the personal costs (in terms of time, risk, etc.) may be high, and the personal benefits may be low and shared with others. The collective action and free rider problems, inherent in so many other areas of law and policy, ring true here as well. Of course there will always be Good Samaritans, but financial incentives, even nominal ones, have proven to be very effective at eliciting information on the margin.[21] Prediction markets have been successful even when non-financial incentives are used, so long as the incentive is something that the trader can use to distinguish himself from others.[22]

The third reason for prediction market success, closely related to the financial incentive reason, is that markets allow forecasts to be weighted according

19. Although aggregating dispersed information might benefit many areas of public policy decision-making, the case is easiest in crime rate forecasting. The fact that information may be disproportionately located in individuals or places outside of the official decision-making hierarchy is something that makes prediction markets especially useful in crime rate and crime policy forecasting.

20. Various barriers to information flow found in other highly complex organizations also plague practical, on-the-job crime forecasting. Consider just some of the various officials and agencies responsible for public safety in a city like Chicago: the Chicago Police Department; the Illinois State Police; the Chicago Transit Authority Police; the FBI; federal marshals; the Bureau of Alcohol, Tobacco, and Firearms; the Drug Enforcement Agency; the Coast Guard; private security guards and police forces at businesses, universities, and homes; police forces from neighboring towns and cities. Each of these entities, not to mention their numerous agents, may have a different private agenda or be prohibited from sharing information about future crime trends in a socially efficient manner. For example, the FBI may learn through confidential informants about a rise in gang activity in a city that is likely to increase homicide and burglary rates, but may not share this with the appropriate local police force because of classic jurisdictional turf battles, to protect the source of the information, for national security reasons, or due to bureaucratic red tape. Or the information may be shared, but in a way that is not believable, is too late to be useful, or with restrictions on how it can be used. In short, the problems that inhibit information sharing among various intelligence agencies or among different departments within a corporation are also evident in public safety enforcement given the multiple jurisdictions and agendas at play. Markets are especially powerful in reducing these types of transaction and coordination costs.

21. *See* Emile Servan-Schreiber et al., *Prediction Markets: Does Money Matter?*, 14 ELECTRONIC MARKETS 243, 243 (2004) (concluding that "real-money markets may better motivate information discovery while play-money markets may yield more efficient information aggregation").

22. In practice, firms use a variety of means, including rankings of points, reputation, and lottery points that can be cashed in for trivial prizes. *See* SUNSTEIN, *supra* note 11, at 117 (describing markets at Microsoft, Google, and other firms, using things like lottery tickets for xbox game consoles).

to conviction. Individuals with views about the future can not only offer their opinion, but also express a confidence in their view by "putting their money where their mouth is," scaling their wager based on their confidence level. An expert willing to back a model of criminal behavior with a financial bet, even a nominal one, is more believable than one that is not willing to make the bet. In addition, an expert's $100 bet is, *ceteris paribus*, more reliable than her $1 bet on the same issue.

The financial nexus between a tipster's information and his or her confidence in the veracity of that information highlights the key distinction between traditional crime prediction methods and crime prediction markets. While deliberation or tip-based models of predicting crime tend to weight each opinion based on the *recipients'* views of the veracity and quality of the information and its provider, markets allow *providers*, who will often have better knowledge of these things, the ability to give weight to their own contribution. This is especially important if one believes, as the Authors do, that in the crime prediction business, recipients are likely to be systematically biased or incapable of accurately weighting information about future crime rates.

Fourth, and of particular interest in the area of prediction markets for policy-making, these markets provide a centralized locus for information aggregation. Today, for instance, if an expert criminologist at State University (or even your Aunt Mary) has information that might be relevant to how many burglaries there will be on Chicago's North Side next week, it is not obvious to whom this information should be revealed or how it should be revealed. Of course both the expert and the layperson can simply call the police with a tip, but the tip will not carry much weight unless it gives authorities specific information about past events or very likely future events. Further, police often dismiss tipsters as crackpots. Police are also inundated with tips of all kinds—real, fake, and self-serving—and unsubstantiated hunches and complicated computer models are likely to be lost in the noise of the station house.[23] The expert might also try to get an audience with, or send a report to, a politician, but the same problems of filtering, and the official's workload exist here too. In addition, Aunt Mary, who might have information of equal or better quality than the expert, is unlikely to get the attention of key decisionmakers.

A public prediction market, however, solves these problems. Anyone with information—whether big or small, based on concrete evidence or simply a hunch—can go to a centralized virtual location on the Internet and place a confidence-weighted bet on the future. Policymakers enjoy a benefit too, since they can look to one particular location (e.g., a web site) for all the information germane to future crime rates. In complex policy-making hierarchies that involve numerous entities with multiple and overlapping jurisdictions, this is especially valuable for top decisionmakers, such as the governor of a state. At present,

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23. "Hunches" is not meant as a pejorative here, as they may be very valuable to the market. This is not only because they may contain valuable information, especially when aggregated with other market participants, but also because individuals trading on weak information add important liquidity to the market—they are the pollen that attracts the bees.

decisionmakers must rely solely on reports from advisors who may in turn be relying on a variety of different estimates or models, each of which may be biased in unknown ways.[24] Prediction markets reduce the cacophony of forecasts to a single estimate that the policymaker can be sure represents the best available forecast. The analogy here is to the stock price of a firm—although the CEO will want to know more about the business she runs than just the stock price, this simple "price" allows her to quickly gauge the collective wisdom of the market. Rarely will the CEO take action solely because the stock price moves, but a move may spurn action and investigation.[25] We envision the same dynamic here.

Finally, markets provide instantaneous and continuous feedback to information providers through prices. This does two things. First, the price (and hence forecast) can change continuously, giving policymakers an always up-to-date assessment of future crime trends—much as the stock market gives economic policymakers a continuously updated assessment of the health of the economy. Second, it gives traders information about the beliefs of other traders, thereby giving them an added incentive to collect and analyze information. For example, if a criminologist sees that the market price forecast anticipates that crime will fall next year in Chicago, but her model shows that a sharp increase is expected, she has a financial incentive to buy (sell) contracts paying off if there is a rise (fall) in crime next year in Chicago. If she does this heavily, thereby causing a change in prices, but then sees the market prices return to prior levels, she might revisit the assumptions in her model or search out what additional information might explain the rest of the market's view. This feature is unique to markets, and is a main reason why markets give better estimates than estimates based on consensus or averages of one-off expert opinions.

B. Extant Markets

Given the theoretical basis and the results described above, it is probably unsurprising that prediction markets have increasingly been adapted to a range of forecasting tasks. The most prominent example is the Iowa Electronic Markets, which has predicted the result of elections more accurately than opinion polls or

24. This problem is bound to be especially salient in crime policy. For one, the current collectors of information about crime—the police, police unions, and police management—may have incentives to manipulate data in a way that serves private over public uses. *See* MOSHER ET AL., *supra* note 18, at 34. For example, police may have incentives to play up the amount of crime in an area in order to attract more resources there or to play up the amount of arrests to show how well they are doing their job. The false data may then be used as inputs to official resource allocation decisions. In addition, given the multiple jurisdictions covering any geographic area, as well as the various public safety agencies in each of these jurisdictions, routing information in an efficient manner is a tremendously difficult task. This is similar to the problem faced by various intelligence agencies after 9/11, which the federal government has been trying to solve with great difficulty. With federal, state, and local law enforcement, each of which has multiple subdivisions, operating within any city or town, the problems of information flow and coordination are bound to be similar in scope.

25. *See* Abramowicz & Henderson, *supra* note 8, at 1361–64.

any other available means.[26] In this forecasting area and others, the academic markets have been joined more recently by for-profit exchanges like Intrade and Betfair.[27] Businesses are also experimenting with these markets, primarily for forecasting sales, input costs, project completion dates, threat of rival products, and potential litigation.[28] Some prediction markets, like those for weather and macroeconomic data (such as the Consumer Price Index) outperform point estimates of experts or consensus averages of experts. For example, Refet Gürkaynak and Justin Wolfers found that the Chicago Mercantile Exchange's Economic Derivatives (Merc) markets yielded more accurate forecasts than the usual "consensus forecast" obtained by averaging the forecasts of a panel of experts.[29] Building on this success, institutional market makers, like the Merc, now host "prediction markets" on topics ranging from the number of days it will frost in a particular month to the number of housing starts in a particular geographical area.[30] It seems inevitable that these markets would eventually find their way from serving as inputs for private actors to data for government policymakers.

Although the federal government's first foray into deploying prediction markets to aid policy analysis—the DARPA-funded terrorism market—was torpedoed for political reasons,[31] prediction markets have recently begun to be proposed and used by academics for informing public policy.[32] Many issues of public policy seem to be driven by randomness, so that while large amounts of data are collected and analyzed by centralized authorities, it is likely that government officials' decisions fail to fully take into account the results of this

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26. *See* Joyce Berg et al., *Results from a Dozen Years of Election Futures Markets Research*, *in* THE HANDBOOK OF EXPERIMENTAL ECONOMICS RESULTS 742 (Charles R. Plott & Vernon L. Smith eds., 2003).

27. Intrade, for example, runs prediction markets on current events, financial topics, politics, and the weather. Intrade: The Prediction Market, www.intrade.com (last visited Jan. 31, 2010). Betfair is similar. Betfair, www.betfair.com (last visited Jan. 31, 2010).

28. *See* Abramowicz & Henderson, *supra* note 8, at 1349–50 (describing early experiments with markets at Hewlett Packard and Siemens, and giving numerous examples of corporate innovators). Within the business sector, technology firms have been particularly quick to adopt prediction markets, and firms such as Electronic Arts, Google, Microsoft, Hewlett Packard, and Siemens have used internal markets to forecast futures sales, whether projects will be completed on time, or the success of unreleased products by both the firms and their competitors. *See* SUNSTEIN, *supra* note 11, at 117.

29. Refet S. Gürkaynak & Justin Wolfers, *Macroeconomic Derivatives: An Initial Analysis of Market-Based Macro Forecasts, Uncertainty and Risk*, *in* NBER INTERNATIONAL SEMINAR ON MACROECONOMICS 2005, at 1112 (Jeffrey Frankel & Christopher Pissarides eds., 2007).

30. *See* CME Group, http://www.cmegroup.com/ (last visited Feb. 19, 2010).

31. *See, e.g.*, Robert Looney, *DARPA's Policy Analysis Market for Intelligence: Outside the Box or Off the Wall?*, STRATEGIC INSIGHTS, Sept. 2003, *available at* http://www.nps.edu/Academics/centers/ccc/publications/OnlineJournal/2003/sept03/terrorism.html.

32. *See* MICHAEL ABRAMOWICZ, PREDICTOCRACY: MARKET MECHANISMS FOR PUBLIC AND PRIVATE DECISION MAKING 34–64 (2007); *see also* Andrew Leigh et al., *What Do Financial Markets Think of War in Iraq?* (Stanford Graduate School of Business Research Paper No. 1785, 2003), *available at* http://ssrn.com/abstract=388762.

analysis. A significant barrier to the implementation of more analytically based policies is the time lag inherent in the process of data collection and analysis—meaning that public officials are frequently presented with information that is significantly out of date. In contrast, market prices are immediate and transparent, and would reduce processing costs, including time.

Consider the flu. The influenza virus kills roughly 36,000 Americans each year,[33] and between $3 and $5 billion is spent each year on prevention, vaccines, diagnosis, and treatment of flu, not to mention lost productivity and other costs.[34] Isolated influenza outbreaks can rapidly morph into epidemics, and thus it is vital for public health officials to have the most complete and up-to-date information available. They do not.[35] The incentives are very high for individuals with information about flu trends to make predictions, but until recently the only forecasting being done, if any, was that of individual doctors or policymakers based on raw, historical data collected and distributed (with a time lag) by the Centers for Disease Control (CDC). The information about future disease activity exists, but according to experts in epidemiology, it is difficult to collect and analyze since it is dispersed and much activity appears to be random.

Accordingly, the University of Iowa, which pioneered prediction markets for political elections, developed and began to operate a flu prediction market. Every Friday during the height of flu season, the CDC publishes a map of the United States, color-coded with five colors to reflect the (recent) historical prevalence of the flu virus in each state, with yellow coding for no activity, green for sporadic activity, purple for local concentrations, blue for regional activity and red for widespread activity.[36] The Iowa Flu market is based on the outcome of this map, with medical professionals across the state buying and selling contracts electronically, attempting to successfully predict what color the state of Iowa will be on the map for any given week. At the end of the influenza season, each trader receives an educational grant equal to the U.S. dollar equivalent of the balance of "Iowa Flu Dollars" remaining in their account. Researchers at the University of Iowa believe that by aggregating the knowledge of medical professionals who see infection taking place on the ground level, they can predict changes in infection levels more efficiently and accurately than government analysts can.

Results from the use of prediction markets to forecast influenza levels are extremely promising.[37] The markets proved more accurate than other methods of prediction based on historical influenza levels for up to four weeks in advance of the target week. Indeed, on average, two weeks in advance of the target week, 50%

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33. Nat'l Inst. of Allergy & Infectious Diseases, http://www3.niaid.nih.gov/topics/Flu/ (last visited Jan. 31, 2010).

34. Stephen C. Schoenbaum, *Economic Impact of Influenza: The Individual's Perspective*, 82 AM. J. MED. (SUPP. 6A) 26, 26–27 (1987).

35. Flu data, which is collected and disseminated by the CDC, is available with at least a one-week lag. *See* Ctrs. for Disease Control & Prevention, Seasonal Influenza, http://www.cdc.gov/flu/weekly/fluactivity.htm (last visited Jan. 31, 2010).

36. Ctrs. for Disease Control & Prevention, Weekly US Map: Influenza Summary Update, http://www.cdc.gov/flu/weekly/usmap.htm (last visited Jan. 31, 2010).

37. *See* Philip M. Polgreen et al., *Use of Prediction Markets to Forecast Infectious Disease Activity*, 44 CLINICAL INFECTIOUS DISEASES 272 (2007).

of observations predicted the correct color, and 100% of observations were one color or less away from the correct prediction level.[38] As one would expect, forecasts improved closer to the relevant measurement period: one week before, the markets predicted the correct color about 70% of the time on average.[39] These results are far superior to any other mechanism used anywhere by anyone.[40]

These flu-forecasting experiments provide a useful analogy for considering crime-forecasting prediction markets. In both domains, the information necessary to set up a useful real-time surveillance and data-gathering system exists, with the key difficulty being how to extract and aggregate the information being seen by individuals (doctors or police) in the field. Standard data collection systems exist, but tend to be backward-looking rather than forward-looking, thereby limiting their usefulness for policy purposes. The challenges of setting up prediction markets are also likely to be similar in each domain, as the idea of trading in markets is somewhat foreign to both healthcare professionals and those in the law enforcement community. Yet in both cases, the gains of more accurate and timely forecasts may be substantial.[41] Before turning to how prediction market data can be used to inform policy-making, we will set the stage by describing the current methods used by policymakers.

C. Current Methods of Crime Forecasting

Crime predictions occur, as they must, within every public safety agency at every level of government. Every agency from the local sheriff's office to the FBI must make forecasts about how much crime and how much of each particular crime is likely to occur in the future. These forecasts help officials determine the amount of crime-fighting resources needed and how to allocate them across the jurisdiction. Our review of current practices reveals that there is an abundance of tools and methods for forecasting, but that these are rarely, if ever, used. And, in any event, they are unlikely to be as effective as those we suggest in this Article.

1. Academic Models

In their book *Is Crime Predictable?*, Carolyn Block and Sheryl Knight attempt to predict future trends in specific types of crime based on data gathered from past criminal activity taking place in the Chicago area.[42] The predictive accuracy of their model varied widely depending on the type of crime in question. For example, rates of larceny and theft were by far the most predictable, with the

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38. *See id.*

39. *See id.*

40. *See id.*

41. It could be argued that this analogy is inapt because viruses are easier to track than the behavior of criminals. While not perfect, it is nevertheless valuable. For one, most existing criminal law forecasting models use inputs like weather, proximity to other crimes, and other crude variables that have reasonable analogs in medical models of infection. In addition, the problem of forecasting is one in which highly localized, private information is dispersed and not currently centralized.

42. CAROLINE REBECCA BLOCK & SHERYL L. KNIGHT, ILL. CRIMINAL JUSTICE INFO. AUTH., IS CRIME PREDICTABLE? (1987), *available at* http://www.icjia.org/public/pdf/ResearchReports/Is%20Crime%20Predictable.pdf.

number of offenses in eleven cities predicted within 10% for the year 1982. In contrast, there were accurate predictions of burglary in only three out of the fourteen cities studied, and predictive success for aggravated assault varied widely, from very accurate predictions to completely unpredictable, depending on the city in question.[43] Ultimately, the authors concluded that the success of their predictions was highly dependent on the quantity of accurate crime data available for crime in a given jurisdiction.[44]

Perhaps the most successful experiment to date is from a study in Britain that re-ran history to predict crimes in the past using new models. Unlike area characteristic studies, the authors based their work purely on the notion that certain crimes, namely burglary, are more likely to be communicable—that is, to occur in neighboring areas over short periods. In this experiment, Kate Bowers, Shane Johnson, and Ken Pease compared three methods for predicting burglaries in and around Liverpool, England.[45]

The first, called "beat hot spotting," is commonly used by police forces around the world. "Beat hot spotting" plots locations of crimes over a certain period of time (say, the past two months) on maps showing the boundaries of different police beats or precincts. The "hot spots" are the locations with the highest concentration of recent crimes, and thus justify more force and attention.

The second, called "retrospective hot spotting," is the most widely accepted method among academic criminologists.[46] "Retrospective hot spotting" involves plotting crimes on an area map, and then applying certain statistical techniques to estimate the density of risk over a specified area (in this case, 200 meters), based on the theory that crimes are more likely inside that area and less likely outside of it.

The final technique, "prospective hot spotting," differs only from retrospective hot spotting in that it weights crimes by time. By assigning weights to crimes based on when they occurred, the prospective hot spotting technique accounts for the fact that crimes (especially burglary, which was the focus of the authors' study) tend to be highly localized in time and space, and are thus "communicable."[47] In this light, the prospective method is far superior to other existing tools, at least for burglary.

The authors show the predictive ability of this approach by re-running history using historical data. They found that had their approach been used, they would have predicted 62% of burglaries within two days, compared with 46% for the retrospective technique, and only 12% for the beat technique.

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43. *See id.*

44. *See id.*

45. Kate J. Bowers et al., *The Future of Crime Mapping?*, 44 BRIT. J. CRIMINOLOGY 641 (2004).

46. *See* Jerry H. Ratcliffe, *Aoristic Analysis: The Spatial Interpretation of Unspecific Temporal Events*, 14 INT'L J. GEOGRAPHIC INFO. SCI. 669 (2000) (discussing the general concept of using past events to generate maps of crime hot spots).

47. The authors show that "the risk of victimization increase[s] for houses within 400 metres of a burgled household for a period of around one to two months, and especially on the same side of the street . . . ." Bowers et al., *supra* note 45, at 643.

Despite these robust findings, we know of no police force that actively uses this modeling approach. In addition, this particular model is limited to one particular type of crime and on a micro scale. It is also just one data point, and while it may be useful when aggregated with other perspectives, on its own it may yield biased estimates due to manipulation, user error, or other factors. For example, burglars might adapt their behavior to foil the model. Therefore, the possibility of using this or other techniques as inputs to a market-based assessment would provide a superior approach while leveraging the strengths of this technique.

2. Real-World Applications

The general idea of using crime-mapping tools has been used by some police forces in large cities to help allocate resources. Perhaps most prominently, New York City has deployed a crime mapping system, known as "CompStat," to assist in resource allocation, strategy formulation, and tactical analysis.[48] Although it is a management philosophy rather than a theoretical, computer-based model, CompStat uses crime data and computer mapping systems as inputs. The basic idea is to use so-called "Geographic Information Systems" to map in real time the location and details of crimes that occur. Decisionmakers can then populate crime maps with demographic data, locations of points of interest—like police stations, schools, and bars—as well as any other information that users consider relevant to crime prediction.[49]

The process of forecasting and evaluation in this context is less technical than managerial, as its use by the New York Police Department (NYPD) and departments in other cities[50] is primarily about framing data and issues for analysis and discussion, instead of creating formulaic and computer analysis of data. The NYPD describes the program as follows:

> On a weekly basis, personnel from each of the Department's 76 Precincts, 9 Police Service Areas and 12 Transit Districts compile a statistical summary of the week's crime complaint, arrest and summons activity, as well as a written recapitulation of significant

48. For a detailed discussion of New York City's approach and its critics, see Heather MacDonald, "Compstat and Its Enemies," City Journal, Feb. 17, 2010, *available at* http://www.city-journal.org/2010/eon0217hm.html. For a study critical of the approach, see Richard Rosenfeld, Robert Fornango, & Eric Baumer, *Did Ceasefire, CompStat, and Exile Reduce Homicide?*, *available at* http://www.cjgsu.net/initiatives/CPP%204-3%20Rosenfeld.pdf.

49. The theoretical underpinnings are based on work in environmental criminology, *see, e.g.*, ENVIRONMENTAL CRIMINOLOGY (Paul J. Brantingham & Patricia L. Brantingham eds., 1981), and routine activity theory, *see* Lawrence E. Cohen & Marcus Felson, *Social Change and Crime Rate Trends: A Routine Activity Approach*, 44 AM. SOC. REV. 588 (1979).

50. This approach is in use in Los Angeles, Philadelphia, and Baltimore. *See*, L.A. Police Dep't, CompStat, http://www.lapdonline.org/crime_maps_and_compstat/content_basic_view/6363 (last visited Feb. 28, 2010); Phila. Police Dep't, CompStat Process, http://www.ppdonline.org/hq_compstat.php (last visited Feb. 28, 2010); Chi. Police Dep't, ClearMap, http://gis.chicagopolice.org/ (last visited Feb. 28, 2010).

> cases, crime patterns and police activities. This data, which includes the specific times and locations at which the crimes and enforcement activities took place, is forwarded to the Chief of Department's CompStat Unit where it is collated and loaded into a city-wide database. The data is analyzed by computer and a weekly CompStat Report is generated. The CompStat Report captures crime complaint and arrest activity at the precinct, patrol borough, and city-wide levels, and presents a concise summary of these and other important performance indicators. These data are presented on a week-to-date, prior 30 days, and year-to-date basis with comparisons to previous years' activity. Precinct commanders and members of the agency's top management can easily discern emerging and established crime trends as well as deviations and anomalies, and can easily make comparisons between commands. Each precinct is also ranked in each complaint and arrest category.[51]

In other words, the system is used as a template to facilitate discussions between local officers and more senior department leadership—it gives *some* facts to support gut-based decision-making.

Accordingly, the process is extremely localized and subject to the idiosyncrasies and biases of the individuals involved. There are no universal formulas, no standards for evaluating crime statistics, and no guarantee that the forecasts will be free from the biases of whatever local decisionmakers think is relevant. Although we are not aware of any systematic data on the success of these mapping systems, their usefulness is limited by the shortcomings of any non-market-based analysis described above. To recapitulate briefly, in this context there are many available mapping systems and models, with no clear best version, let alone a formula for applying the tools in a successful way. The federal government has invested some resources to try and overcome barriers to implementing existing forecasting tools. The most obvious use of this investment is a series of conferences at which academics and public safety officials share data.[52] The bounty of these conferences is promising but reinforces our earlier

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51. For a detailed discussion of New York City's approach, see http://www.nyc.gov/html/nypd/html/chfdept/compstat-process.html.

52. For example, the National Law Enforcement & Corrections Technology Center was founded in 1994 as part of the National Institute of Justice with the mission of providing "support, research findings, and technological expertise to help State and local law enforcement and corrections personnel perform their duties more safely and efficiently." *See* Justice Technology Info. Network, http://www.justnet.org/Pages/home.aspx (last visited Feb. 25, 2010). The Center's Crime Mapping & Analysis Program provides technical assistance and training "in the areas of crime and intelligence analysis and geographic information systems." *See* Nat'l Inst. of Justice, http://www.ojp.usdoj.gov/nij/maps/ (last visited Jan. 31, 2010). It allows crime analysts, who might work in civilian agencies or be uniformed officers, access to shared knowledge and resources about the "best" available means of forecasting crime. There are also some crime analyst trade associations that provide support. *See, e.g.*, Int'l Ass'n of Crime Analysts, http://www.iaca.net (last visited Jan. 31, 2010); Bair Software – Our Company, http://www.bairsoftware.com/about/index.html (last visited Jan. 31, 2010). There are also free web sites that offer both advice and some rudimentary mapping tools. For example, www.crimereports.com is a "national crime mapping and citizen alerting site, free

observation about the usefulness of markets as an aggregating tool in a world in which there are numerous available tools but no best tool. There are innumerable sources of information,[53] but it is clear that the information is not being aggregated.[54] It also shows the challenge that any decisionmaker must face when thinking about crime forecasting—there are perhaps too many choices and options without sufficient data or experience to indicate the optimal strategy.[55]

Despite the significant research on the subject in the past fifty years, no widely accepted method for predicting criminal activity has emerged. As with influenza statistics, it is still a formidable task to publish information that is timely, accurate, and in a format that can be understood and used by law enforcement personnel working on the ground level. Indeed, because the task of transforming much of criminological research from an academic exercise to actionable information presents a difficult obstacle, many decisions taken by professionals seem to be based on "gut instinct" rather than fact-based analysis.

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for any law enforcement agency nationwide." In addition, there are numerous conferences where academics and law enforcement officials interact to discuss new tools and techniques. The "Ninth Crime Mapping Research Conference" was held in 2007. At this conference, experts from universities presented new software tools.

53. Another source of data and analysis is the National Insurance Crime Bureau (NICB). The NCIB is a private trade group of over 1000 insurance companies that has investigators and analysts who try to identify crime patterns and hot spots relevant to the insurance of life and property. As far as we are aware, the NCIB and other similar groups do not share their information, models, or analyses in any systematic fashion with public safety officials or other analysts. We speculate that there are many other private entities like NCIB doing similar research that would be useful inputs to prediction markets on crime rates. This is just another example of how information that might be valuable to policymakers is dispersed and siloed in inefficient ways.

54. A variety of public-facing tools for citizens and policymakers are also available through web-based mapping programs. There are websites where anyone can access crime statistics on neighborhood maps for cities including Chicago, San Francisco, Indianapolis, and Philadelphia. For example, on www.chicagocrime.org, citizens can type in a street address, and immediately see the location and details of crimes committed in the vicinity over specified time periods. These websites suggest several interesting conclusions. For one, there already exists a lot of freely available and up-to-date data on crimes that have been committed. The problem does not seem to be a lack of data but a lack of useful analysis. These data and websites can be useful for the markets we envision because they are inputs and data that anyone from experts to citizens can use to inform their trades. These websites also show that there is a demand for these data among the general public, who will be vital to creating a liquid market that will produce interesting results. Numerous providers are available, but not all of them have complete data or coverage. For example, one of the authors tried to use one site to collect information on crime in his neighborhood, and got an error message saying that the local police department did not provide data to the site. Finally, all of these sites, like most of the crime analysis being done in law enforcement agencies, are backward looking. A citizen of Chicago, Philadelphia, or New Hampshire can find out (maybe) what crimes were committed in these places, but not the most up-to-date thinking on what crime is likely to happen soon or in the future.

55. Prediction markets may make these conferences less necessary because the knowledge of crime experts can be shared and aggregated electronically instead of in person.

With this abundance of data and analytical shortcomings as background, we turn to our contribution to this field.

II. PREDICTION MARKET FORECASTS FOR CRIME AND CRIME POLICY

A. Crime Forecasting Basics

Crime forecasting research has been largely academic and consists almost entirely of mapping and modeling historical data to geographical areas, demographics, and external factors, such as weather or time of day. Although these point estimate models are undoubtedly useful, they are, for the reasons discussed in the previous part, of only very limited use. Moreover, we are aware of no crime prevention authorities using such tools to make predictions either about (1) localized crime trends (for example, what the crime rate will be in a particular area of the city in the next two weeks) or (2) longer-term crime trends (for example, what the crime rate will be in a state over the next decade). To our knowledge, crime policy setters, such as governors, attorneys general, and mayors, are not using these models either.

Very simple markets can be designed for both purposes, and their output is likely to be much simpler to comprehend and much more accurate than any existing models or practices. For instance, imagine that a policymaker—say one setting sentencing policy or allocating budgets for future prosecutorial and prison functions—wants to determine the best estimate of the violent crime rate in a particular geographical area for a future year. The policymaker could offer a contract that pays $1 if the violent crime rate for the year in question is between twenty and twenty-five victimizations per thousand people (and $0 otherwise).[56] The market could also include other potential ranges, such as ten to fifteen, fifteen to twenty, twenty-five to thirty, and thirty-five to forty, and so on, with similar payoffs. Specifying the entire range of probable outcomes has the advantage that the market not only reveals an expected future crime rate but also a complete probability distribution. This would allow the policymaker to determine the most likely outcome and level of uncertainty of the forecast, and to give appropriate weight to both upside and downside risks.

Individuals with information, a guess, or an intuition about the crime rate would then trade based on their views about the relative value of the contract and its current trading price. For example, if an academic criminologist who has built an econometric model estimating a violent crime rate in Illinois of thirty to thirty-five victimizations per thousand residents sees that the price of a contract for this prediction is trading at $0.45 (meaning that the market believes that this crime rate is about 45% likely to occur), she may buy these contracts until the price reaches her confidence level in the model. On the other side of the transaction may be a police chief in Chicago who has seen crime levels in historically high-crime areas falling dramatically, and who believes this to be a secular trend. He may sell (or sell short) contracts for the thirty to thirty-five range, while simultaneously buying

56. Since the bet is effectively $1 or $0, these contracts are called "binary options."

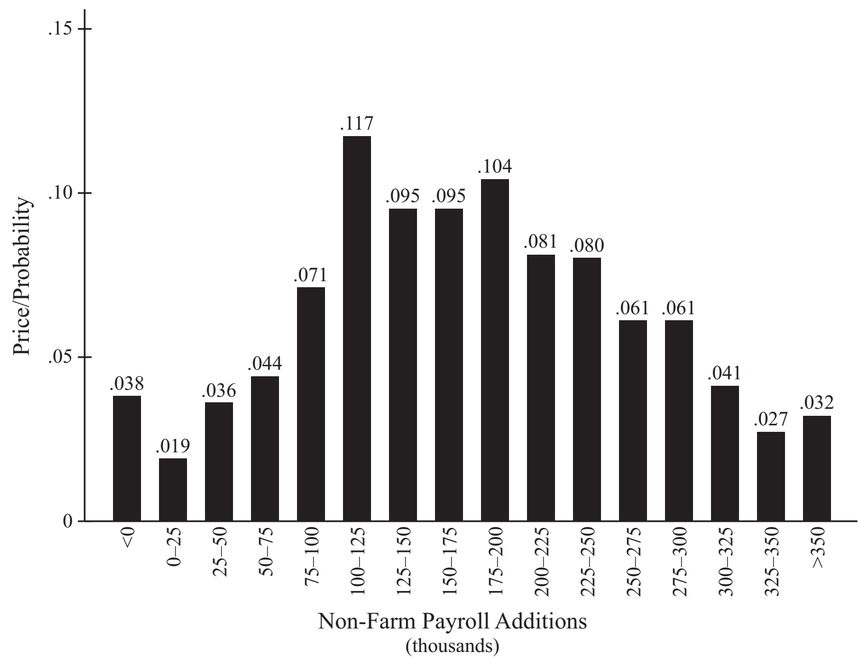
contracts in the ten to fifteen range, which is what his gut tells him is the right answer.[57] Trades like these, and innumerable and uncharacterizable others, will take place while the market remains open, allowing not only an aggregation of various estimates but also a feedback mechanism that allows continual updating. As noted above, the evidence from other forecasting domains suggests that this mechanism will likely yield superior forecasts to other alternatives.

Not only are the prediction market estimates an improvement in terms of forecasting, they also add a useful probability dimension to any forecast. As noted above, using a range of potential future outcomes as contract reference points not only allows policymakers to assess the most likely outcome, but also permits policymakers to estimate the most likely range of outcomes, as well as the relative weight of risk from higher or lower results than the mean expected result.

Work by Refet Gürkaynak and Justin Wolfers illustrates an analogous example from the economic forecasting domain, specifically expected job growth. Figure 1 shows the price of various securities that would pay $1 if employment growth in May 2005 fell into specified ranges. The graph shows that traders were willing to pay $0.117 for the option paying $1 if payroll growth was between 100,000 and 125,000 jobs. This implies a market probability of about 11.7% for this result. This distribution suggested that 174,600 jobs were expected to be added to non-farm payrolls, but that there was significant uncertainty around this estimate, with a 95% confidence interval extending from 0 to 350,000 jobs.

57. Two things about this stylized example, where there are traders on both sides of a particular transaction, are worth exploring. First, in these markets traders are typically anonymous, so that no individual knows with whom he or she is trading. It is possible that some markets could be designed to reveal the identity of the traders, since this might have signaling benefits. These issues have been discussed elsewhere in a related context. *See* Abramowicz & Henderson, *supra* note 8, at 1349–50. Second, the example assumes an open-auction style market, in which buyers and sellers are matched by a market maker (usually an automated computer system), but there are many other potential market designs. *See generally id.* at 1350–54. For example, the Chicago Mercantile Exchange, Goldman Sachs, and Deutsche Bank, and others have set up new markets in "economic derivatives," which are designed to predict macroeconomic data like the number of jobs created or the number of housing starts in which alternative market structures are used. One of the most common is the pari-mutuel system in which individual bets are aggregated without having a seller or buyer on the other side. *See id.*; *see also* Gürkaynak & Wolfers, *supra* note 29, at 14.

Figure 1:
Auction on Non-Farm Payrolls for May 2005
Held June 3, 2005



B. Simple Crime Forecasting

Applying the general tools described above to crime forecasting is a logical next step given the importance of this issue and the lack of an accepted methodology for making predictions today. In many of the other areas mentioned above—including interest rates, product sales, weather, and political elections—prediction markets serve as an aggregator of different expert opinions and methodologies, a mechanism for improving deliberation among experts, and a sanity check on expert views. Crime prediction is at a more basic stage, as there are no consensus estimates from experts as to what the crime rate will be in some future period. Expert opinions are diffuse, untested, and remote from policymakers. In addition, crime prediction is an area where localized knowledge by laypersons can provide real value to the market, unlike, say, interest rates. We will leave a description of the specifics of the policy process to others, and will discuss only those issues that are particularly relevant when considering the role of market-generated forecasts.

1. Forecasting the Past

For simplicity, we begin by noting one very simple (but potentially useful) role for prediction markets: they can be used to "forecast" history. Crime analysts are often forced to wait for months before official crime statistics are released, and this is often too late for them to be relevant for analysis or forecasting. For example, the FBI publishes an annual report—*Crime in the United States*—that aggregates data from nearly 17,000 law enforcement agencies.[58] This report tells us, for instance, that there were 25,314 burglaries in the City of Chicago in 2005.[59] The report for 2006 was not issued until September 2007, however, making the data less useful for policymakers at the national or local level than it would be if real-time data or estimates were available. A quicker release of the data (or forecast thereof) would allow some decisions for the current or next year to be made based on the most recent experiences in a city or state. Thus, a prediction market forecasting what the FBI or Bureau of Justice Statistics will eventually publish as last year's crime rate can provide a very useful interim estimate.[60]

2. Simple Forecasts of the Future and the Feedback Loop

A more ambitious program might involve the use of a forward-looking prediction market for informing resource allocation decisions. Assuming that the maximand for policymakers is crime reduction, and the only short-term lever for implementation is the number of police officers to allocate to a particular area, officials may allocate greater or fewer numbers of police officers to a particular area based on the market's predictions. For instance, if a market of experts, political leaders, law enforcement agents, and local citizens believe that crime is expected to rise in the north of a city, but not in the center, this might suggest re-allocating police to the north. This behavior would be consistent with policymakers' objectives and—assuming market predictions are accurate—would presumably lower crime in that particular area.

But, this approach is not without difficulties. Traders will understand that a higher price of contracts predicting high crime levels in the north will lead to a police response, which may lead to lower crime in that area than would be predicted, and therefore cause traders to lower their forecasts of crime in the north. This is the feedback loop problem.

The extent of this feedback loop depends on the perceived responsiveness of policymakers. If policing levels are thought to be entirely unresponsive to forecasts, then there is no feedback at all. At the other extreme is market equilibrium. If policing levels respond sufficiently to prediction market prices, then market participants understand that policymakers are working to ensure that no area sees disproportionately high crime, and hence the market will predict equal

58. *See* FBI, Uniform Crime Reports, http://www.fbi.gov/ucr/ucr.htm (last visited Jan. 31, 2010).

59. *See* FBI, Offenses Known to Law Enforcement: Illinois 2005, http://www.fbi.gov/ucr/05cius/data/table_08_il.html (last visited Jan. 31, 2010).

60. Similarly, prediction markets could be used to forecast future data revisions by the official agencies. There is evidence in some contexts that the market is quite good at incorporating forecasts of future revisions into market prices. For example, Alan Krueger and Kenneth Fortson show that while financial markets respond strongly to new employment data, they do not respond to revisions to previously released data, suggesting that markets had already forecast these revisions. *See* Alan B. Krueger & Kenneth N. Fortson, *Do Markets Respond More to More Reliable Labor Market Data? A Test of Market Rationality*, 1 J. EUR. ECON. ASS'N 931 (2003).

crime rates in all areas of the city—regardless of the presence or absence of factors that influence crime. Intermediate cases between these extreme assumptions will yield intermediate predictions, and the variance in forecasts will be attenuated by the possibility of a partial response in policing levels. To be clear, the problem here is not in the quality of the forecasts—and in the examples considered above, the market may well yield accurate forecasts, both in terms of being unbiased and in terms of statistical accuracy. Rather, the subtle issue considered here relates to how forecasts might serve as an input to the policy process.[61]

A first-cut solution to this problem would be to run a forecast based on a "no policy change" scenario. For example, a prediction market could be set up that forecasts the burglary rate in the north, south, and city center in some future period assuming that current policing decisions (for example, the number of police assigned to each precinct and the number of patrols) were to persist within some specified tolerance range. This could be implemented by trading contracts tied to future crime levels, but with the proviso that all bets are cancelled if policing levels changed. Such a market would in fact reveal the market's expectation of crime levels in the future period, conditional on current policing levels persisting until that future period.

This solution, however, raises a further set of difficulties, as traders might ask what circumstances would lead policymakers to keep policing allocations unchanged. Presumably current policing patterns are likely to persist only if current crime patterns also persist over the relevant time period. In this way, while the market will in fact forecast precisely what was asked of it—*certain crime rates conditional on current policing patterns persisting*—this forecast reveals a confluence of underlying crime factors and the policy reaction function.[62] The result is a feedback loop that may make it difficult to interpret prediction market prices. After all, changes in underlying crime factors will have both a direct effect

61. Indeed, this difficulty is not unique to prediction markets, as all forecasts must be based upon some assumption about the future of the policy variables (in this example, the policy variables are policing levels by district). In the example considered above, the prediction market prices forecast the expected levels of crime across space, taking account of the "policy reaction function"—the expected response of policymakers to this forecast. Thus, these forecasts incorporate forecasts of both underlying crime factors, and the responsiveness of policymakers.

62. The difficulty here is quite familiar in the economic context; as forecasts of interest rates by both bond markets and professionals reflect the convolution of underlying economic forces and also the expected response of the Federal Reserve to these shocks. As Greg Mankiw recently wrote:

> This might seem circular: The Fed is responding to the market, and the market is responding to the Fed. But there is nothing wrong with that. Economists are used to simultaneity. Of course, the market will catch on to the policy, but that's okay. In fact, it is ideal. We end up in a fixed-point equilibrium in which the market expects the Fed will hit its inflation target. In this equilibrium, the market's forecast of interest rates will tell the Fed what it needs to do to accomplish what it wants to accomplish.

Greg Mankiw, *How to Decentralize Monetary Policy*, GREG MANKIW'S BLOG, July 16, 2006, http://gregmankiw.blogspot.com/2006/07/how-to-decentralize-monetary-policy.html.

(raising the forecast level of crime) and a partly offsetting indirect effect (as traders in prediction markets respond to the likelihood that policymakers will respond to this shock, thereby lessening its influence).

The possibility that crime forecasts are joint forecasts of crime factors and policy responses, however, is not fatal to the enterprise of using market-based or other forecasts for policy purposes. There is a simple way of resolving the feedback loop or simultaneity problem.

To see this, consider the case in which the crime rate in a jurisdiction is a function of the underlying level of criminality and the policy response from public safety officials. In a world with robust crime rate prediction markets, we would expect policymakers to set a policy response based on two imperfect forecasts of the underlying level of crime: a traditional forecast model and the forecast from the prediction market. But the prediction market is not predicting underlying levels of criminality but rather crime rates, which are influenced by the expected policy response, which is in turn influenced by the prediction market price.

This again is the feedback loop problem. The prediction market price is based on an estimate of crime rate conditional on an estimated level of underlying criminality, but that crime rate includes a policy response to the very prediction market price that is being generated. As shown mathematically in the Appendix, we can solve this series of simultaneous equations for the relationship between the prediction market price and underlying crime factors so that we can resolve the feedback loop.

Rather than slog through the math here, we simply summarize the key implications of the model and relegate the details to the Appendix. First, if policymakers respond to the traditional, non-market forecast, the response of the prediction market forecast to a rise in underlying crime is muted by the expected response of policy to offset this expected rise in crime. If the policy fully offsets any shocks to underlying criminality, then the crime rate will not be revealing of shocks to the underlying crime factor, and hence the prediction market price provides no information about the underlying crime factor. In the more realistic case in which shocks are less than fully offset, the model shows that the prediction market price provides useful, albeit attenuated assessments of levels of underlying criminality.

Second, if policymakers respond (somewhat) to the prediction market prices, responses to rises in crime will be further attenuated. But an important output of this model is that as long as the policymaker does not respond infinitely strongly to prediction market prices, there will still be a positive (albeit attenuated) relationship between the prediction market price and the underlying crime factor. This means that prediction market prices are still valuable for policymakers, even when policy reacts aggressively to underlying crime factors.

From this simple model, we can take away the following. Prediction market prices will respond to changes in the underlying criminality or crime factors, but not one-for-one. This is because: (1) prediction market participants don’t have perfect foresight; (2) policymakers respond to rises in a certain underlying crime factor (X) as forecast by the traditional approach, and this reduces the effect of X on the ultimate crime rates; (3) policymakers respond to the prediction market, further reducing the effect of expected rises in crime factors on crime rate; and (4) prediction market participants understand all of this. Thus, if policy responds to forecasts of crime, this will tend to attenuate the extent to which prediction market prices reflect changes in the underlying crime factor.

To return to our concrete example, if some underlying crime factor is expected to lead burglary in the north of the city to rise by 10%, markets may expect the policymaker to respond by sufficiently raising the police presence to partly offset this risk. As such, the prediction market may only suggest that the number of burglaries in the north of the city will be higher by 3%. This means that the market believes that the policy response will, on average, reduce the number of burglaries that would be expected if police policy persisted, but not by an amount sufficient to keep the number of burglaries unchanged. When reading the market data, policymakers should be aware of this feedback loop, and should respond to this forecast of a 3% higher burglary rate *as if* it is forecasting a 10% higher burglary rate, and respond accordingly. If the policymaker responds to the degree anticipated, then the number of burglaries will rise by only 3%, despite the fact that underlying factors shifted enough to raise burglaries by 10%. As long as the market knows with some certainty the likely reaction of policymakers, this can lead the market to an efficient estimate of crime rates, since traders can incorporate the reaction into their forecasts, and policymakers can unpack forecasts and expected policy responses when setting policy.

To be more concrete, suppose that the Chicago Police Department has, through the Mayor's office, a long-term target for the burglary rate, and announces (or simply follows) a policy of allocating police resources in a specific and set manner. For example, if the market expects the burglary rate to be higher than the target, allocate more resources than the market expects; if the market expects the burglary rate to be lower than the target, allocate fewer resources than the market expects. The result is an equilibrium in which market forecasts help to inform policymakers about appropriate resource allocations.

C. Using Markets to Inform Policy

The most important questions for crime policy—ones that the simple prediction markets discussed above are not designed to address—involve the efficacy of different types of crime-reduction interventions. The policy-relevant questions include whether to devote greater resources to police on the street, or to incarceration; whether to focus efforts on social programs, or on developing a robust low-wage labor market; and the relative cost and benefits of curfews, anti-gang efforts, or the death penalty. These questions are about identifying the *causal effect* of various interventions.

There are two ways in which prediction markets can be helpful in identifying these important structural parameters. The first we call a *prediction market event study*; the second involves *contingent prediction markets*.[63]

63. *See* Joel Slemrod & Timothy Greimel, *Did Steve Forbes Scare the US Municipal Bond Market?*, 74 J. PUB. ECON. 81, 81 (1999) (examining impact of Forbes's

1. Prediction Market Event Studies

The term "event study" comes from finance, where it is a tool commonly used to determine the causal significance of a particular event—like a press release—on a firm's stock price. These studies are premised on the idea that the price of a stock reflects an informed forward-looking assessment of the company's prospects. So, for instance, if a firm decides to purchase a competitor and the announcement of this decision is accompanied by an increase in the firm's stock price, it is likely that the market believes that the acquisition will raise the firm's profits. An event study can be used to isolate the effect of the announcement from other influences on the firm's stock price.

By analogy, the "price" in a crime prediction market reflects an informed forward-looking assessment of the rate of a particular criminal activity. As discussed above, a prediction market designed to predict the number of homicides in Illinois in the next year will generate a market price for contracts paying $1 for each potential outcome. This price represents the market-based probability of that particular outcome. Given this market, one could perform a prediction-market event study looking to see if the announcement of, say, a death penalty moratorium led the market to forecast higher or lower homicide rates.[64]

It is worth comparing the event study methodology with a more traditional econometric analysis of observational data. In the traditional approach, one might examine annual data on homicide rates and changes in death penalty legislation, and if a negative correlation were found, infer that the death penalty caused lower homicide rates.[65] This is not the only possible inference. It is also possible that political support for the death penalty is driven by the level of the homicide rate, or that changes in both political support for the death penalty and homicide were driven by some third factor. The existence of alternative explanations undermines any policy conclusion from an event study, since it would be impossible to determine the *cause* of the drop in homicide rates. This problem plagues current scholarship on the impact of the death penalty, causing the estimates about deterrence to be widely inconsistent.[66]

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probability of winning presidency in prediction markets with prices in bond markets); Erik Snowberg et al., *Partisan Impacts on the Economy: Evidence from Prediction Markets and Close Elections*, 122 Q.J. ECON. 807, 807 (2007) (using prediction market event study to examine the effect of election results on economic variables); Wolfers & Zitzewitz, *supra* note 9, at 122–24 (discussing results from markets designed to predict the effect of political and economic events on the 2004 presidential election).

64. It is worth emphasizing that an event study does not reveal the actual effects of the policy but rather a market-aggregated forecast of the likely effects of the policy.

65. *See, e.g.*, Hashem Dezhbakhsh et al., *Does Capital Punishment Have a Deterrent Effect? New Evidence from Postmoratorium Panel Data*, 5 AM. L. ECON. REV. 344, 344 (2003); Isaac Ehrlich, *The Deterrent Effect of Capital Punishment: A Question of Life and Death*, 65 AM. ECON. REV. 397, 398 (1975).

66. *Compare* Cass R. Sunstein & Adrian Vermeule, *Is Capital Punishment Morally Required? Acts Omissions and Life-Life Tradeoffs*, 58 STAN. L. REV. 703, 706 (2005) *with* John Donohue & Justin Wolfers, *Uses and Abuses of Statistical Evidence in the Death Penalty Debate*, 58 STAN. L. REV. 791, 792–94 (2005).

Causation is easier to isolate over short time intervals, since the narrower the window of time in which a market reaction is gauged, the less chance that some other factor may have caused these sharp changes in expectations. Prediction market event studies can compare market reactions just before and after policy change announcements, which allow for cleaner causal inference. For example, a prediction market of future homicide rates could include an "event study" test of the effect of the announcement of a death penalty moratorium. This event study would measure estimated future homicide rates minutes before and after the announcement of the moratorium, and thereby gauge the market's estimate of the "value" of the moratorium on homicide rates.

An obvious problem here, as in all short-term event studies, is that the market may have factored into the pre-announcement market price some probability that the event to be tested would occur. So, if a prediction market is running on the issue of future homicide rates in Illinois, and Illinois announces a moratorium on capital punishment, there might be no change in the homicide market if the market already "knew" that the governor planned to issue a moratorium.[67] This may lead to the mistaken inference that the policy would have no effect. It is possible, of course, to look back to see changes in market prices that might reflect leakage of information, but this is no more than guesswork. In a less extreme case, if the markets had already assessed an 80% chance of a death penalty moratorium, then the event study will reveal a rise in expected homicides that is only one-fifth as large as the true causal effect of the moratorium, as four-fifths of the effect had already been priced in.

There is a solution to this problem that can be achieved by using a combination of prediction market event studies. Using the death penalty moratorium again as an example, imagine that we ran a parallel prediction market on whether or not Illinois would abolish the death penalty. One could then combine data from both an Illinois homicide rate prediction market and an Illinois death penalty moratorium prediction market to derive an estimate of the causal effect of a death penalty moratorium on the homicide rate. Very simply, the causal effect of a policy can be measured as the expected change in crime rate (from one prediction market) divided by the market estimate about whether the policy change will be adopted (from another prediction market).[68] Thus, if the announcement of a moratorium led the markets to revise upward (downward) its homicide forecast by 10% and the market assessment of a moratorium rose 70%, we can infer the market believes the impact of the moratorium on homicides would be an increase

67. One need not believe entirely in the strong form of the efficient market—that all information, whether public or not, is incorporated into market prices—to accept that imparted information will often be baked into market prices. Something of significance, like a death penalty moratorium, will be debated in public, or, if in private, will involve a sufficient number of persons so as to raise the possibility of official or unofficial leaks, or even just forward-looking political forecasts.

68. In notation, this is: Δ*crime forecast* / Δ*probability the policy is adopted*. A necessary pre-condition to this generalizable conclusion is that one must find a useful "event" to study, that is, one in which the probability of a policy being adopted changes in a sufficiently discrete way.

(decrease) in homicides of 14%.[69] The ability to isolate such causal parameters through multiple markets is a key advantage of prediction markets.

In addition to providing more accurate causation analyses than observational econometric event studies, prediction market event studies can also assess the likely causal impact of events or policies that have not and may not ever happen. Under the econometric approach, one can only study the effect of policies that have actually been implemented and observed. Under the event study approach, all that is required is a "shock" to the likelihood that a policy will be adopted. For instance, it may be that the election of a particular candidate for governor will increase the likelihood of a death penalty moratorium, and hence it would be instructive to also analyze the effects of the election on the crime prediction markets.

At this point, a word of caution is in order. In many cases, identifying a clean "shock" may be particularly difficult. For instance, it may be that the election of a particular candidate for governor, who would raise the likelihood of a death penalty moratorium being implemented, raises the likelihood of more restrictions on the use of certain investigative tactics or force by police. If so, the crime prediction markets may respond to changes in the likelihood of both policies, leading the event study approach to confound the effects of executions and those of police tactics. In other words, the credibility of an event study depends crucially on identifying plausibly exogenous shocks to the policy being examined. Therefore, the biggest practical difficulty with the event study approach is that it is confined to issues for which there are useful "events" or "policy shocks." In the next section, however, we address a potential solution that can overcome this limitation.

2. Simple Contingent Markets

In a contingent market, individuals trade contracts whose payoffs are linked *both* to the likelihood of a policy change and to subsequent levels of crime. Contingent markets can use very simple math to determine the expected impact of a particular policy choice on crime. Continuing with the example above, consider that the governor of Illinois is contemplating a death penalty moratorium, and she wants to know the best estimate of the impact of this policy choice on homicide rates. The governor could review the vast literature on this subject, counting studies for and against moratorium, perhaps weighted by the fame of their authors or the rigor of the analysis performed. She could also ask for a report from a blue-ribbon commission comprised of experts in the field and politicians of note. These are surely sensible things to do, and we should hope that politicians would be thoughtful about decisions of this magnitude before they make them.

However, there are weaknesses to these traditional methods that make them inferior to the market design postulated below. The work involved in bringing a recommendation to the governor may be corrupted by the private agenda of her staff or biased by the political conclusion the governor "wants" to

69. Calculated as 10% change in crime forecast based on moratorium divided by 70% probability of moratorium = 0.14.

reach. For sure, the process is unlikely to produce a full or complete picture of the debate, since even the most wisely chosen commission or staff is unlikely to bring all available points of view to the table. In addition, as shown by the work of Cass Sunstein and others, group decisions, either by the governor's staff or the commission, are inferior to market-based mechanisms because of the potential for polarization, hidden profiles (i.e., individuals with information may not reveal it for social or psychological reasons), and other factors.[70]

Markets, on the other hand, allow for constant deliberation and anonymous information-giving. This means that new information is instantly revealed and priced into the market, and that individuals can update their views based on the market price and market reactions to new information. And public markets are transparent in ways that even the most open and public commission inquiries cannot be. Given the recent history of contentious battles over various high-profile policy debates, including issues of executive privilege and the public's ability to know what goes on behind closed doors, any tool that increases the transparency of the policy deliberation process without undermining the potential to reach a positive result is a good thing.[71]

Now let us consider an example of how a policy market might work. The Illinois governor could learn about the deterrent effect of the death penalty by floating four contracts on a prediction market, each paying $1 if in some future year one of the following occurs:

> (a) There is a death penalty moratorium and homicide rates are higher than today;
>
> (b) There is a death penalty moratorium, and homicide rates are lower than today;
>
> (c) There is no death penalty moratorium, and homicide rates are higher than today; or
>
> (d) There is no death penalty moratorium, and homicide rates are lower than today.

These markets could be run in a variety of ways, but one potential design (consistent with current methods for making public policy) would be to limit the participants to a set number of experts, law enforcement officials, academics, notable citizens, community leaders, politicians, and so on, but to post the prices on a government website, thereby allowing the public to have a continual window into the "market's" view on the question. One benefit of this transparency is that it would encourage political accountability—politicians who opt to ignore the market would likely have to build a strong case for their position.

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70. *See* SUNSTEIN, *supra* note 11, at 65.

71. The two most famous examples from the past two decades are the energy task force led by Vice President Cheney, *see* Cheney v. U.S. Dist. Court for D.C., 542 U.S. 367, 391–92 (2004) (holding for administration in a lawsuit involving challenge to lack of openness in proceedings), and the health care task force led by First Lady Hillary Clinton, *see* Ass'n of Am. Physicians & Surgeons, Inc. v. Hillary Rodham Clinton, 997 F.2d 898, 916 (D.C. Cir. 1993) (ruling in case challenging openness of proceedings).

Based on the trading prices of the four securities described above, we can determine the market's view of the impact of the moratorium (or the deterrent effect of the death penalty) by interpreting the prices of each of these securities as probabilities. To determine the market's combined view of the impact of the moratorium, we would want to compare the probability that homicide rates will be lower with no death penalty with the probability that homicide rates will be lower with a death penalty. From the four securities, these probabilities are:

> *Probability that homicide rate will decrease with no death penalty = b/(a+b); and*
>
> *Probability that homicide rate will decrease with death penalty = d/(c+d),*

where *a* equals the price of contract (a) above, *b* equals the price of contract (b) above, and so forth. If the death penalty is in fact perceived to be a significant deterrent, the latter probability should be substantially lower than the former.

Consider a numerical example: assume that the price of security (a) (moratorium & higher homicide rates) is $0.60; the price of security (b) (moratorium & lower) is $0.20; the price of security (c) (no moratorium & higher) is $0.30; and the price of security (d) (no moratorium & lower) is $0.70. We can conclude the probability of a reduction in homicides with a death penalty moratorium is 25% (.20/(.60+.20) = .25), and the probability of a reduction in homicides with the death penalty is 70% (.70/(.30+.70) = .70). This would suggest that *the market believes* there is a strong deterrent effect from the death penalty, since the probability that the homicide rate will decrease is forty-five percentage points higher with the existence of a death penalty.

3. Advanced Contingent Markets

This is, of course, not the only potential prediction market that can be used to answer policy questions, such as the death penalty example above. Parallel prediction market contracts with policy contingencies can also help unpack the causal impact of particular policies. For instance, one could float a pair of forward contracts with the policy choice (*X* or *not-X*) imbedded in each. Both contracts would have payoffs tied to a prediction of future crime rates, but one would pay off only if an enumerated contingency comes to bear (*X*), while the other would pay off only if the contingency does not happen (*not-X*). The policy contingency could be increased policing, different sentence lengths, new rehabilitation or treatment programs, or the use of capital punishment.

To continue with the death penalty moratorium example, the governor who is interested in determining the best guess about the deterrent effect of the death penalty in Illinois could create a market with two prediction market contracts, Class A and Class B. Both Class A and Class B contracts pay (at the end of the market) $1 for each homicide that occurs in a particular year in the future. But Class A contracts pay out *if and only if* Illinois has the death penalty (and all bets are refunded if Illinois does not have the death penalty), and Class B contracts pay out *if and only if* there is a death penalty moratorium. As such, the prices of these two prediction market contracts should reveal the expected number of homicides with the death penalty in force and the expected number of homicides without the death penalty.[72] The difference between the prices of these prediction market contracts (at any time) reveals the extent to which the market anticipates a higher or lower homicide count as a result of a death penalty moratorium.[73]

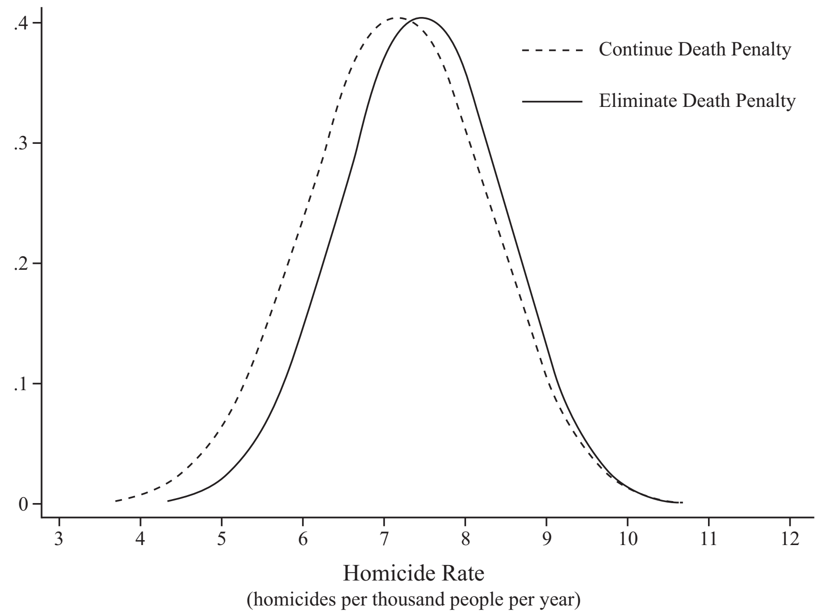
While this design yields a useful point estimate of the market's view about the impact of a policy change, it says little about the precision of the estimate.[74] Other market designs can help policymakers understand the uncertainty surrounding the market's estimate. Consider an alternative design: a prediction market is created with a series of contracts that pay $1 if a trader accurately predicts *both* the homicide rate and whether Illinois has the death penalty. For instance, one example would be a contract paying $1 if Illinois has the death penalty in a particular future year *and* the homicide rate is between 7 and 8 per 100,000 people in that year. The contract would stipulate that if the first part of the contract is not fulfilled—such as where Illinois does not have the death penalty in the future year—then those trades are simply refunded. These markets would reveal the full probability distribution of likely homicide rates under both a death penalty regime, and under a moratorium. Figure 2 illustrates using artificial data.

72. In simple notation: (*E[Homicides | Death penalty]*); and (*E[Homicides | Death penalty moratorium]*).

73. If there were 650 homicides in Illinois in 2006, and the market believes the number will stay about the same in the absence of a death penalty moratorium, the Class A contract should trade at around $650. If the market believes that homicides will increase (decrease) by 10% in the event of a moratorium, then the Class B contract would trade for $715 ($585). The difference between the prices of these two contracts specifies this market estimate of the impact of the moratorium.

74. Or, more fully, the precision of the market's conditional expectations.

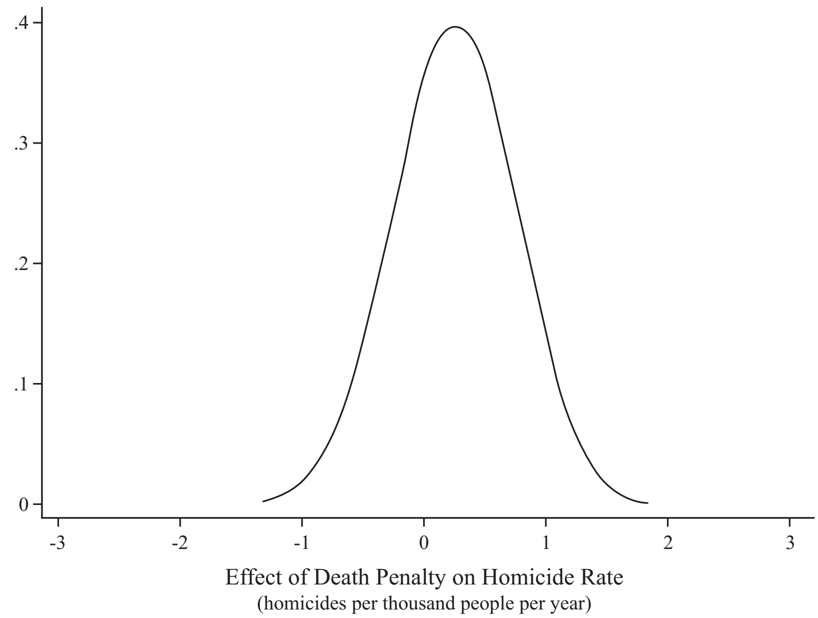
Figure 2:
Prediction Market Forecasts of Homicide Rate Under Alternative Scenarios



This chart reveals the market's assessment of the probability of each outcome under the two alternative policies. Importantly, these probabilistic assessments can then be combined to reveal not just the market's assessment of the most likely impact of eliminating the death penalty, but also the full distribution of risks. More formally, the market-assessed probability distribution function of the homicide rate with the death penalty is shown in the leftmost panel; we denote this *f(h,1)*. The next panel shows a similar distribution, denoted *f(h,0)*, for the no-death-penalty scenario. The effects of eliminating the death penalty, *x*, are also uncertain, and the likelihood of various impacts is given by the probability distribution function *g(x)*. If the effects of death penalty elimination are additive and uncorrelated with the remaining surprise in the crime rate under the status quo, then the uncertain impact of the death penalty can be derived as the deconvolution of the two market-assessed probability distributions.[75] This is shown in Figure 3.

75. That is, by Bayes Rule, $f(h,1) = \int f(h',0) \cdot g(h-h') \cdot dh'$

Figure 3:
Prediction Market Forecast
Implied Effect of the Death Penalty



The key advantage of this analysis is the ability to see the entire distribution of potential outcomes from the use of the death penalty or other policy choice. Existing assessments of death penalty policy rely on comparisons of point estimates (that is, the mean of these distributions). For example, the classic death penalty deterrence study is one in which comparisons are made of average homicide rates one year prior to and one year after a moratorium or abolition.[76] A leading study uses this approach and concludes that each additional execution decreases homicides by about five.[77] Another study by Dezhbakhsh, Rubin, and Shepherd used a system of simultaneous equations and county-level panel data that covered 3054 counties for the 1977–1996 period.[78] Their models were designed to assess the effects of the death penalty by analyzing fluctuations in crime rates immediately after a death sentence is carried out, by using moving averages to measure the conditional probability of execution, given a death sentence, and then explore effects on the crime rate. They found that each execution prevents about eighteen homicides on average.[79] More recent studies find some ambiguity in the

76. *See* Hashem Dezhbakhsh & Joanna M. Shepherd, *The Deterrent Effect of Capital Punishment: Evidence from a "Judicial Experiment*,*"* 44 ECON. INQUIRY 512, 518–519, tbls.3 & 4 (2006) (using data from 1960 to 2000).

77. *See id.*

78. Dezhbakhsh et al, *supra* note 65, at 359.

79. *Id.* at 361.

data on homicide rate averages, concluding that "the existing evidence for deterrence is surprisingly fragile, and even small changes in specifications yield dramatically different results."[80] Those studies base their argument on the fact that the death penalty has been "applied so rarely that the number of homicides it can plausibly have caused or deterred cannot be reliably disentangled from the large year-to-year changes in the homicide rate caused by other factors."[81] All of these studies use historical data and average homicide rates.

The advantage of the contingent prediction markets we propose in this paper is the ability to compare full probability distributions in a way that makes policy choices more informed, since the full range of potential outcomes is revealed instead of just the mean of the distribution. For example, it may be that the mean change from the elimination of the death penalty is negligible, but that the distribution of outcomes changes dramatically and with downside risks that are untenable for policymakers. Existing studies do not offer this potential form of analysis.

These conditional markets also exploit the true power of prediction markets, in that they elicit the expectations of market participants even about states of nature that do not currently (and may never) exist. As such, it is not necessary for Illinois to actually implement a death penalty moratorium, or for a police chief to actually reallocate resources to a particular type of crime, to use prediction markets to study the likely effects of doing so.[82] It is this feature that makes conditional markets so promising for counterfactual policy analysis. One obvious problem remains—distinguishing correlation from causation in these markets—and we turn to this next.

4. From Correlation to Causation

We have shown how contingent markets can be useful for revealing market-aggregated assessments of conditional expectations, for example, what the homicide rate will be in Chicago if the governor institutes a death penalty moratorium. While these contingent markets solve the difficulty of generating expectations of various correlations, they do not in any way solve the problem of distinguishing correlation from causation. Markets might predict changes in the variable being measured—homicide rates—but this could be because of facts unrelated to the policy change being studied by the market. Continuing with the death penalty example, if we observe the market predicting an increase in homicides if a death penalty moratorium is implemented by the incoming governor of Illinois, it may be because the market believes the moratorium will lower the cost of murder, leading to more of them on the margin. Or it may be because the market believes the governor will generally be "soft on crime," thereby lowering

80. Donohue & Wolfers, *supra* note 66, at 794.

81. *Id.*

82. It bears repeating that these markets do not predict the *actual outcome* of the underlying question being forecast, but rather represent the market's best guess as to what the outcome will be. In any policy-making process, a market forecast is likely to be one input of many. Our claim is simple: a well-designed prediction market will likely yield as good or better estimates than any other available method.

the costs of all crime, leading to more crime, including murder, on the margin.[83] As such, the market's expectation of a positive correlation between the death penalty and murder rates may not reflect a causal link.

A common econometrical solution to this problem is to exploit "natural experiments"—that is, to analyze the effects on the policy in question by measuring the effects of clearly exogenous shocks to policy. What is needed is an unexpected policy change that is not associated with potentially confounding variables. This shock would, like the prediction market event studies discussed above, allow a cleaner test of policy causation than a policy change that was correlated with potential confounding variables. The potential to use this widely accepted methodology is even greater with contingent prediction markets, since market designers can create their own shocks through contract design.[84]

We propose the use of markets, called "Prediction Instrumental Variables," (Prediction IVs),[85] that allow policymakers to simulate exogenous policy shocks as a way of testing the causal significance of the shock.[86] The first step in creating these markets is to think of a plausible and exogenous shock to the policy variable. For example, a U.S. Supreme Court ruling banning capital punishment would certainly be an exogenous shock to death penalty policy. This sudden change would affect both death penalty and non-death penalty states, and without the potentially corrupting variables of changes in state administration of the laws. The death penalty states would provide the data for testing the policy change (a death penalty moratorium) while those states without an active death penalty statute would be a useful control group. One could then collect data on how much execution and homicide rates changed, by state, and then compute a simple Wald Estimator of the causal effect of the execution rate on the homicide rate:[87]

> *ß = (average Δhomicide rate in death penalty states — average Δhomicide rate in non-death penalty states) / (Average execution rate in death penalty states$_{before}$).*

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83. We mean nothing by this politically, as the authors are likely not of one mind about any of the underlying policy issues that prediction markets could be used for in this area. This is just a stereotype, of course. In reality it was a *Republican* governor that implemented the death penalty moratorium in Illinois, and a *Democrat* governor that reinstated the death penalty.

84. The obvious difficulty with analyzing policy shocks, like a federal ban on the death penalty, is that one can only analyze those shocks that actually occur. But a key advantage of contingent markets is that one can recover expectations of a conditional expectation, even on contingencies that never occur.

85. "IV" here stands for "instrumental variable."

86. *See* Justin Wolfers & Eric Zitzewitz, *Five Open Questions About Prediction Markets*, *in* INFORMATION MARKETS: A NEW WAY OF MAKING DECISIONS IN THE PUBLIC AND PRIVATE SECTORS 13–14 (Robert W. Hahn & Paul C. Tetlock eds., 2003).

87. This Wald Estimator representation is equivalent to a two-stage least squares set-up, running a first-stage equation: *Execution rates after — Execution rates before = α Active death penalty statutes before*, and in the second-stage, estimating *Homicide rates after — Homicide rates before = β Predicted ΔExecution rate + γ*.

In the real world, such instrumental variables (IVs) are not freely available, and indeed, the Court has not provided an experiment like this since 1972.[88] In addition, exogenous shocks that are interesting enough to be studied may be so severe—as in the case of a federal ban on the death penalty—as to render the policy debate, at least at a state political level, moot. In other words, state policymakers would want to know *before* a federal ban whether a death penalty moratorium is likely to increase, decrease, or have no effect on murder rates.

The prediction markets we have in mind, however, are not disabled by either of these shortcomings. Prediction IVs enable policymakers to ask a prediction market what is expected to occur *if the shock happens*, whether or not it will happen. Instead of waiting for the Supreme Court to ban the death penalty, in which case it is too late anyway, a policymaker could create a prediction market to trade two contracts that estimate the expected deterrent effect of the death penalty:

> *Contract A*: Pay $1 for each percentage point rise in the homicide rate from 2008 until 2012 in current death-penalty states, with the proviso that the bet is only active if the Supreme Court rules that the death penalty is unconstitutional;
>
> *Contract B*: Pay $1 for each percentage point rise in the homicide rate from 2008 until 2012 in current non-death-penalty states, with the proviso that the bet is only active if the Supreme Court rules that the death penalty is unconstitutional.

Contract A pays $1 for every percentage point increase in crime in death penalty states if the death penalty was ruled unconstitutional, and if it is not, trades would be unwound. The market should therefore price Contract A as the expectation of the crime rate in death penalty states conditional on the death penalty being unconstitutional. Contract B is the same, except it applies to the non-death penalty states. So the difference in the prices of Contract A and Contract B is essentially the market's expectation of what a differences-in-differences estimate of the effect of the death penalty ban will be in 2012, conditional on there being a ban. These markets yield a market-based prediction of the *causal* effect of executions on homicides. Some very simple math gives us a formula that policymakers can use to measure causal impact.[89]

For example, the population of states with the death penalty is about 260 million people, and these states had a homicide rate of about 5.5 per 100,000

88. *See* Furman v. Georgia, 408 U.S. 238 (1972).

89. This simplifies to: *ß=(a-b)/average execution rate in death penalty states 2008*. The numerator tells you crime will rise (fall) a certain percent faster in death penalty states than non-death penalty states if the death penalty is banned, so hence the death was deterring (encouraging) a certain number of crimes. The denominator scales the estimate. (The denominator would normally be the difference in the execution rate in DP and non-DP states. But since executions are of course zero in non-DP states, this difference is just the number of executions in the DP states.) Dividing by the number of executions before the death penalty ban tells you how many crimes are being deterred for each execution.

people for 2005, meaning there were about 14,000 murders in these states.[90] The contracts described above can help determine the deterrent effect of the death penalty in these states. Say that Contract A was trading at $6 and Contract B was trading at $2. In this case, the market expectation is that a death penalty ban would cause a 4% increase in homicides, or an extra 560 murders as a result of the ban. To figure the deterrent effect of the death penalty, we divide the number of extra homicides by the number of executions. There were 32 executions in 2006,[91] so the market view of the deterrent effect would be about 18 homicides deterred per execution.[92]

Similar markets can be imagined in a variety of crime forecasting and policy areas. Exogenous shocks could be changes in sentences for particular crimes, changes in gun laws, the deployment of ubiquitous security cameras, the allocation of additional crime-fighting resources, and so on.

III. DESIGN ISSUES

While the previous Part discussed possible uses of prediction market prices in the policy process and some potential market designs, we now turn to discussing the "engineering issues" involved in actually setting up useful markets in this area. We only touch on some of the key issues for these markets, given time and space constraints.

A. Contractability

For any trade to take place, "contractability" is needed, meaning that the contract must clearly present the policy question at issue, while being specific and detailed enough to be enforceable in a low cost way. If a contract is vague or can be interpreted in more than one way at its resolution, the market will result in disputes and indeterminate outcomes, since traders' actions in the market might have been based on an interpretation of the contract that was inconsistent with its actual intent. Consider the following prediction market designed to estimate future crime rates: "this contract pays $1 for each percentage point drop in crime-related deaths in Chicago from 2008 to 2012." This contract cannot create a legitimate prediction since it is unclear what a "crime-related death" is, how it will be measured, what data will be used to resolve the market, what is meant by "Chicago," and so on. A better, but perhaps not perfect, contract might say: "this contract pays $1 for each percentage point drop in homicide rates for Chicago, Illinois, as reported in the initial estimate of 2009 homicide rates issued by the FBI Uniform Crime Reporting program." As this example shows, all contracts must specify a date by which the forecast event must occur, a measurement technology,

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90. Homicide rates and population are based on 2005 data. *See* FBI, CRIME IN THE UNITED STATES 2005 (2006).

91. Ten states executed prisoners in 2007. *See* Dealth Penalty Information Center, http://www.deathpenaltyinfo.org/article.php?scid=8&did=186 (last visited Feb. 25, 2010). Texas accounted for 60% of all (state and federal) executions in 2007. *See id*. The other states carrying out death sentences were: Alabama (2); Arizona (1); Georgia (1); Indiana (2); Ohio (2); Oklahoma (2); South Carolina (1); South Dakota (1); and Tennessee (1). *See id.*

92. This is simply: (6-2)/32 = 0.13.

and a mechanism for determining whether the forecast event occurred. There are, however, no easy answers to the questions of contract design, and some trial and error will be inevitable. To aid states and local governments interested in running these markets, we include in our "modest proposal" below a suggestion that the federal government take the lead on encouraging these markets, including consideration of potential contract terms. These markets could then be tweaked at the non-federal level, allowing the many governments and law enforcement agencies to be laboratories for contract design experimentation.

Because policymakers likely care more about abstract measures, like levels of "public safety," than individual indicators of them, contractability constraints would seem to limit the usefulness of these markets. Although the police chief may be interested in knowing how many burglaries are likely next year, it is more likely that policymakers at City Hall, in the legislature, or even in the police department, are more interested in whether public safety is expected to improve or decline in the next year. So ideally one would run a market predicting the overall level of public safety, but this would suffer from the obvious shortcomings of measurability and ambiguity discussed above. Clever contract design, however, can overcome these constraints. So while we can't imagine a contract paying based on how "safe" Chicago is, a contract linked to whether a majority of the population will answer that "they feel safer this year than last" in a future Gallup Poll would be robust enough for a prediction market. There are a variety of existing surveys that could be used for this base-lining function.

The use of a neutrally determined baseline, such as those provided by polls or expert reports, can be used to dramatically expand the power of policymaking prediction markets. For example, the National Academy of Sciences publishes periodic reports on issues such as whether the death penalty is a deterrent. These expert reports, drawn on the best thinking of experts in the field, are conducted in a manner designed to yield a deliberative answer that improves on any individual expert view, and that is insulated to some extent from politics. A prediction market could run the outcome of the next report. So, while one cannot run markets directly on whether "the death penalty is a deterrent," one can float contracts paying $1 if "the next National Academy of Sciences panel on the death penalty concludes that the evidence of a deterrent effect is not persuasive." Even if such a report is not planned or expected for some time, the market would provide an estimate of the current best thinking on the issue. There are obvious problems with this from a contractibility perspective, such as the need for a third-party judge to interpret the text of the report.[93] But we believe these can be overcome. There

93. Contractability issues can turn out to be surprisingly subtle and difficult to forecast in advance. For instance, the online prediction market InTrade.com offered a contract on whether Yasser Arafat would depart the Palestinian state by the end of 2005, and there was some controversy on whether the departure of his corpse would count as his departure. On a lighter note, newsfutures.com offered markets that paid off "if Harry Potter is alive at the end of the novel 'Harry Potter and the Deathly Hallows'." Subsequently there was some controversy on how the claim would be settled if an epilogue to the book described Harry Potter as dying of natural causes after a long and happy life. As a final example, the Iowa Electronic Markets floated contracts linked to the number of seats won by each party in the 1994 Senate elections, and settlement of these contracts was

are numerous prediction markets currently operating with similar or greater amounts of ambiguity, and the market makers do not have to frequently unwind trades or settle disputes.

Another key issue regarding contract design is whether there is useful information to be aggregated. Aggregating mechanisms are only valuable when there exists useful information held among diverse and numerous individuals, and the aggregation process will collect it without biases that mislead or use selective information.[94] As a result, if the information that diverse market participants provide through trading does not improve upon publicly available information, because perhaps it is less tangible, less trustworthy, or less relevant, it is doubtful that the market could improve on any official forecast. For example, InTrade.com floated contracts on whether weapons of mass destruction (WMD) would be found in Iraq, and in April 2003 these markets wrongly predicted that it was very likely that weapons would be discovered by mid-2003. Because these weapons can be non-existent everywhere in the view of market participants and yet still exist, disperse information about their non-existence was unlikely to overturn the strong case made by the White House.

In the crime policy prediction markets we propose the problem of diverse market participants not improving on publicly available information is unlikely to be a barrier to successful markets. For one, the predictions generally will not be running up against official pronouncements about the future, as in the case of the Iraq WMD issue. While the government does issue actual historical results, the markets will pre-date these, and in fact will be designed to predict them. It is unlikely that markets would therefore be systematically biased by government announcements. In addition, many individuals with access to the markets will have information relevant to the questions being examined in the market. As discussed above, criminologists, law enforcement personnel, doctors, neighbors, and criminals themselves possess information that when aggregated by a prediction market is likely to exceed any information held by any single individual or group. This is especially true since these traders can be expected to use a myriad of sources and types of data, including expert models, police officers' observations, the gut feeling of observant residents, what the doctors in the emergency room are seeing, what the lawyers trying cases know about law enforcement levels, and what the prison wardens or guards see among prison populations.

B. Contract Choice

There are three basic contract types, and each can yield different insights into the market's beliefs, revealing a probability, mean, or median. We have used two of these three so far. First, there are binary option contracts in which a winner-take-all market will pay $1 if a specific event occurs. An example might be a contract paying $1 if the FBI reports a homicide rate in 2012 that is higher than 6 homicides per 100,000 of population. The price of this contract can be interpreted

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confounded by the fact that Senator Richard Shelby switched sides to become a Republican the day after the election (and before all results were finalized).

94. This is the classic GIGO principle—Garbage In, Garbage Out—that impacts any information aggregation tool.

as a market-aggregated probability that the event—an FBI report of this murder rate—will occur.[95] As we have shown above, a family of such contracts (paying if the homicide rate is 0–1, 1–2, 2–3, 3–4 and so on) will yield a full probability distribution. Second, there are linear index contracts with payoffs that vary one-for-one with the event that one is trying to forecast. An example might be a contract that pays $1 per homicide that occurs in 2012 as reported by the FBI. The price of this contract will reveal the expected number of homicides.

Finally, in "spread" betting, traders do not bid on the price of a contract, but rather on the cutoff that determines whether an event occurs. For example, the market maker stipulates that the price of the contract is $0.50, and it pays $1 if the homicide rate is higher than some cutoff, y. All of the parameters of this contract are pre-determined, except the cutoff y, which is determined in the market by trading behavior.[96] An even-money bet reveals the market's expectation of the median outcome, and hence can be interpreted as a forecast that the homicide rate is as likely to be higher than y, as it is to be lower than y. If instead, the contract costs $4 and pays $5 if the homicide rate exceeds y, then this will elicit a value of y that the markets believe to be a four-fifths probability. Analogously, one can design spread contracts to elicit any particular percentile of the probability distribution of future outcomes. As such, this may be a particularly useful form of contract when policymakers are interested in confidence-interval forecasts.

The design of contracts should take into account likely market imperfections, including transaction costs and behavioral anomalies. Consider an example of each. Although prediction markets can be created in ways that make the actual costs of trading extremely low,[97] some contract types may have commitment costs that would reduce the liquidity of the market. Linear index contracts, for instance, may provide little incentive to trade relative to transaction costs. To see this, consider a contract that pays $1 for each homicide committed in Chicago in 2010 as reported by the FBI. The market price for this contract is $500, meaning the market is predicting 500 homicides in that year. An individual trader learns of very strong information that the number of homicides is likely to be 505. It is very unlikely that the individual will trade based on this information, since she must commit $500 to the market for each $5 she expects to gain. The market would then get stuck at an inaccurate, but fairly close, estimate of the actual outcome. In light of this problem, it is probably no surprise to note that winner-take-all binary contracts have proven much more popular with traders in most prediction markets.[98]

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95. *See* Justin Wolfers & Eric Zitzewitz, *Interpreting Prediction Market Prices as Probabilities*, (NBER Working Paper No. 10359, 2007), *available at* http://www.nber.org/papers/w12200.

96. The most popular example of spread betting is point-spread betting in football, where the bet is whether or not a team will win by at least a certain number of points.

97. Iowa markets work with hundreds of dollars total committed.

98. This problem can be seen in prediction markets for political elections. If the market is, say, predicting the share of the two-party vote in an election, a winner-take-all binary contract will be far more effective at encouraging trading.

Behavioral anomalies that can disable markets generally also have the potential to cause problems with prediction markets.[99] One that is particularly troubling for prediction markets is the tendency for people to be very poorly calibrated at differentiating small probability events from *very* small probability events. This leads very small probability events to be priced as small probabilities, suggesting that market prices particularly close to zero (or one) may be biased. This anomaly is a key feature of Kahneman and Tversky's Prospect Theory, and indeed, the bias toward overbetting on tiny probabilities is strongly evident in many gambling markets as a "favorite-longshot bias."[100] With this evidence of mispricing of very small probabilities in hand, it seems likely that markets may be poorly calibrated to small probability crime events. For most crime forecasting markets we have discussed, this is not likely to be problematic, because crime rate forecasting does not involve very small or even small probabilities.

For questions that the market maker believes involve very small probabilities, simple reframing of contract terms can help yield more useful data. For example, suppose policymakers are interested in multiple-victim shootings and want to know whether they are likely to happen in Illinois. A contract paying $1 if there is such a shooting in Illinois in January involves small or very small probabilities, and may be subject to this longshot bias. A market that pays $1 if Illinois is the next state to experience a multiple-victim shooting may be better calibrated. Here again we see how clever contract design can be used to expand the efficacy of these markets.

C. Market Scope

The value of prediction markets comes from the fact that they aggregate information, but thus far we have not described precisely what information would be aggregated. This is really a question about who should participate in these markets. It seems clear, for instance, that one would want to ensure that the markets reflect both the macro-level insights of criminologists and the street-level intelligence of police around the country. This does not necessarily mean that individual officers have to be permitted to trade because presumably a lot of their information would be aggregated by police chiefs.[101] There are complicated tradeoffs here that cannot be resolved in theory but only in practice. For example, issues of sabotage or other market manipulation, the potential for trading to distract from job performance, the creation of skewed incentives, and so on are all present in decisions about who to include in the market.

As a general matter, we would suggest that there should be a presumption against ever limiting participation in markets. The reason for this presumption is

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99. *See* SUNSTEIN, *supra* note 11, at 123; Abramowicz & Henderson, *supra* note 8, at 1350.

100. *See* Richard H. Thaler & William T. Ziemba, *Anomalies: Parimutuel Betting Markets: Racetracks and Lotteries*, J. ECON. PERSP., Spring 1988, at 161, 163; Eric C. Snowberg & Justin Wolfers, *Explaining the Favorite-Longshot Bias: Is it Risk-Love or Misperceptions?*, NBER Research Paper (2007), *available at* http://bpp.wharton.upenn.edu/jwolfers/research.shtml#FLbias.

101. This suggests that it may be important to try to recruit traders through groups such as the Police Executive Research Forum.

simply that those designing markets often do not know where the most valuable information resides. Indeed, if policymakers knew precisely who had information about future crime trends, it would probably make more sense to simply interview those experts than to run prediction markets. Thus, one of the roles of prediction markets is to provide incentives for those with relevant information to identify themselves. Similarly, allowing broad access to the market also increases the liquidity in the market, and while even very small-scale prediction markets (involving as few as a dozen or so traders) have yielded useful forecasts, larger markets are likely to yield more accurate forecasts.

This is in part because of the presence of uninformed traders. While including "noise traders" might be expected to add only noise to prediction market forecasts, it is the presence of uninformed noise traders that provides an incentive for better-informed traders to actually participate in the market.[102] The presence of uninformed traders also provides an incentive for informed traders to invest in further information discovery and research, likely making the market more efficient.

Despite the presumption toward unlimited access to trading, there are three important reasons that one may want to limit the universe of traders in a crime prediction market. First, prediction markets do not simply aggregate information; they broadcast it to anyone who can see the market price. If the relevant information one seeks to aggregate is classified, such as FBI intelligence on terrorist threats, then these secrecy needs can be respected only by allowing those with a sufficient security clearance to trade in the markets.

Second, substantial asymmetric information, and, in particular, insider trading may destroy the incentive to trade in a market. For instance, allowing the staff who compile the Uniform Crime Reports (UCR) to trade in prediction markets tied to the yet-to-be-released UCR data gives them a tremendous advantage. If other traders fear that the person on the other side of a transaction may already know what the crime rate is, they will be reluctant to trade. If the information asymmetry is strong enough, no trades will occur at all. Barring the insiders from trading, however, comes at a cost: arguably the most useful information is not aggregated.[103]

Third, there may be other very real practical reasons to limit participation in a market, such as where a research sponsor subsidizes trades, or where limiting participation is the price of obtaining regulatory approval for the market.

Finally, as mentioned above, allowing certain types of individuals to trade may have positive and negative externalities on job performance, community

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102. *See* Albert S. Kyle, *Continuous Auctions and Insider Trading,* 53 ECONOMETRICA 1315, 1326 (1985) (describing role played by noise traders in creating incentives for informed traders to trade in the market).

103. For an interesting proposal for dealing with insider trading within firms, see Robin Hanson, *Insider Trading and Prediction Markets*, (George Mason Univ. Working Paper 2007), *available at* http://hanson.gmu.edu/insiderbet.pdf (proposing several options, including, designating some informed insiders as "well-informed traders" and requiring them to preannounce trades when dealing with less well-informed traders).

policing, and neighborhood relations. These are real issues that will be worked out only through practical experiments and trials.

One reason that is often offered for limiting market participation that we find unpersuasive is that there is a risk of sabotage or manipulation of the market by bad actors. In the area of crime, as was the case for the scuttled terrorism market, this concern may be a real political roadblock. As policymakers might not want to give the impression that criminals could somehow "profit" twice from their crimes (the crime and the market profits), or be encouraged to commit crimes to achieve profits in the prediction markets. While politically sensitive, we believe these concerns are largely overblown.

As discussed fully elsewhere,[104] sabotage and manipulation are a risk in all markets, but there is nothing inherent in crime prediction markets that provides added incentives. Given the very small stakes we imagine will be sufficient to produce meaningful outputs, a criminal would be foolish to take on added real-world risk in order to earn profits on the order of hundreds or even thousands of dollars. This is especially true when one considers that criminals will not know the underlying factors affecting the market's movement. In any event, any individual criminal will have a negligible impact on the total number of crimes being forecast.[105] Finally, public safety officials can monitor trades to some extent, especially large and suspicious trades, in the way that securities markets and the SEC monitors stock trades. In this way, suspicious trades or traders that earn large profits can be important signals of potential criminal activity, both in the market and in the real world.

As for the unclean hands argument—that criminals should not be allowed to participate in these markets—this too is politically sensitive but ultimately a red herring. Criminals of all sorts have very valuable information about future crime patterns, and unlocking this information and aggregating it with other information is a major motivation for some of these markets. Although it may seem untoward to have criminals participating, giving them some quid for the quo of contributing information is not morally or ethically different from plea bargaining, reducing sentences for testifying against confederates, treating snitches well, and a variety of other police and prosecutorial tactics. In fact, markets are likely to give more high-powered incentives for information sharing since they are anonymous, have a financial incentive, and can be used to filter out bad information. Snitches do not have incentives to lie or mislead in markets, where the information is bound to be corrected by other market participants with better and contradictory information.

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104. *See* Abramowitz & Henderson, *supra* note 8.

105. Sabotage possibilities exist in all markets, but they are extremely rare. After all, criminals can currently sell short the shares of any number of public companies and then act to destroy their value. We tolerate the slight risk of this because of the existence of criminal deterrence and because of the benefits of such markets. Moreover, if prediction market stakes are set at relatively low levels, the gains from manipulating the market will be dwarfed by the likely criminal penalties.

D. Liquidity

A key practical concern held by many about prediction markets is that they may not be able to generate sufficient liquidity to make prices truly reflect a market-based aggregation of all available data. Perhaps this is not unexpected, as a famous economics proposition, the "no-trade theorem,"[106] predicts that no two rational profit-motivated agents will ever trade with each other. The intuition is simply that each will trade only if they believe themselves to be at an informational advantage to the other; thus, if one reveals a willingness to bet, this may lead the other to question their belief in their own informational advantage, hence becoming unwilling to bet.

In practice, the assumptions underlying this theorem are often violated, and a range of other motivations may lead someone to trade. Our evidence on this is partial and collected across a range of prediction contexts. For instance, risk love, or the "thrill of the gamble" clearly motivates huge amounts of trade on sporting events. While forecasting crime may never be as thrilling as forecasting the outcome of a football game, recent growth in political prediction markets and other areas suggests cause for optimism.[107]

Career concerns provide another useful motivation for trade. For instance, when prediction markets in economic indicators were established in 2004, many financial market economists were asked by their employers whether the firm should now trade directly based on their forecasts. Anecdotal evidence suggests that at least a few felt that they had to trade in order to signal their belief in their own ability.

More generally, reputation may play a key factor in stimulating trade. While Google operates an internal prediction market with real money rewards, their traders report that they are really motivated by the possibility of being declared the top trader in a specific quarter. Indeed, the success of play-money exchanges like the Hollywood Stock Exchange suggests that feelings of community, or reputational concerns, can be quite important. The more public and formal the system of prizes, the greater the incentive it can yield. For instance, finance students at Wharton compete in a play-money stock market prediction market, and many of the top performers list their scores on their resumes, suggesting that there is an employment-related payoff. This seems like a useful

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106. P. Milgrom & N. Stokey, *Information, Trade and Common Knowledge*, 26 J. ECON. THEORY 17, 27 (1982).

107. Political prediction markets, such as those offered by companies like Intrade and Betfair, as well as those run by academics, pollsters, and others, are now commonly cited in analyzing political races. *See, e.g.*, John Stossel & Maxim Lott, *Foretelling the Future: Online Prediction Markets*, ABC NEWS, May 9, 2008, *available at* http://abcnews.go.com/Business/Stossel/story?id=4813558&page=1. In fact, prediction markets are now viewed as important enough signals of future outcomes that interested parties are trying to manipulate them. In a famous incident during the 2004 presidential election, someone tried to manipulate the market, which was showing John Kerry losing to George Bush. The attempted manipulation did not work. *See* Donald Luskin, *Who's Behind the Bush-Futures Attacks?*, NAT'L REV. ONLINE, Oct. 18, 2004, *available at* http://www.nationalreview.com/nrof_luskin/luskin200410181132.asp.

idea for a crime prediction market, as a formal system of trader recognition may well enhance the reputations of particularly accurate criminologists.

Finally, a very simple way to stimulate trade is to provide a direct financial incentive. A simple method would involve a market sponsor directly funding the accounts of traders with the sponsor only able to withdraw funds after a trading threshold has been met. A more indirect method would involve the market maker setting up a specific trading account designed to lose money. Thus, by offering to bet randomly, the house can effectively turn the prediction market from a zero-sum game for traders into a positive-sum game. By analogy, the same incentive for informed traders to participate exists if it is not the market maker losing money, but instead some uninformed third party. Indeed, this is one of the reasons why (perhaps paradoxically) the key to generating substantial trade can be in attracting uninformed traders, because they provide the incentive for the informed to trade, thereby revealing their information.

E. Legal Concerns and Practical Tradeoffs

Finally, legal, ethical, and political concerns still may pose something of a barrier to the adoption of prediction markets for crime forecasting, particularly in the United States. On the legal side, it is essential that a crime prediction market not violate relevant anti-gambling laws at both the state and federal levels. One innovative solution used by firms has been to have the employer provide the endowment for each individual's trading account, under the theory that if one can win but not lose, then one is not gambling. An alternative approach involves the use of play-money markets, perhaps supplemented by some prize for the traders with the highest play-money bankrolls at the end of each quarter.

In terms of ethical (and hence political) concerns, Alvin Roth notes that moral repugnance about certain types of market transactions often constrains the development of market institutions.[108] He notes that a prominent role for money can trigger repugnance, but that with creative market design, the role for money can be minimized.[109] Thus, despite widespread repugnance at the possibility of a market in kidneys, if two patients each have willing but incompatible donors, an in-kind exchange is perceived as quite acceptable. Similarly, the possibility of profiting from terror was perceived as sufficiently repugnant that an effort within the Department of Defense to set up prediction markets related to geopolitical risk led to a political furor and the cancellation of that program.[110]

These examples suggest the need for a careful assessment of the political implications of a crime-forecasting prediction market. Again, careful design can help frame the relevant issues. While it may be repugnant for a trader to profit from a homicide, equivalent transactions in life insurance markets trigger no such reaction. Alternatively, while some may find it repugnant to profit from death, few

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108. Alvin E. Roth, *Repugnance as a Constraint on Markets*, J. ECON. PERSP., Summer 2007, at 37.

109. *Id.*

110. *See* Robin D. Hanson, *Designing Real Terrorism Futures*, 128 PUB. CHOICE 257, 257 (2006) (noting that much of the political opposition was not in fact to any of the markets that the researchers involved actually proposed).

would argue with giving crime forecasters with a strong track record greater recognition. Thus, play-money markets are much less likely to trigger repugnance and, hence, political difficulties.

If these political, legal, and ethical constraints are insurmountable, the implication is not that crime forecasting should continue in its current form. The key insight from the emerging literature on prediction markets is that the wisdom of crowds often performs better than so-called experts. While markets may be superior to most alternatives, related methods for tapping the wisdom of crowds (such as polls, the Delphi method, and competitive forecasting) may outperform the status quo. More research is needed on these methods.

IV. Conclusion and a Modest Proposal

Prediction markets provide intriguing possibilities for better crime forecasting, both in the realm of predicting crime rates and patterns as well as the evaluation of crime policies. While their use has never been tested in this domain, evidence from other types of prediction markets strongly suggests that they may yield better forecasts of future crime levels and certainly would permit more active experimentation in public safety strategies. On this latter point, we believe that contingent markets can be used to establish market-based assessments of the likely causal impact of alternative interventions, thus allowing policymakers to outsource much of the policy-making to market forces. In many other domains of government, these decisions are already made through a market-based mechanism.

We mentioned the use of market forecasts in setting monetary policy, but the concept is broader than this. For instance, in something as mundane as government contracting, the contract for paper supply is open to bids from competing firms. While economists typically emphasize the allocative role of these auctions, a bid can also be thought of as a bet that the contractor can source paper at the price offered. Similarly, a bid in a prediction market is a bet about some useful piece of information. In the contracting domain, the service-providing and information role of markets are bundled—whoever wins the auction has to provide the government with the paper. In the criminal justice setting, one may not want to leave service delivery (such as policing) to the market, but prediction markets offer the possibility of markets continuing to play a complementary informational role, perhaps in helping to determine the allocation of police resources most likely to reduce crime.

With what we believe is a strong case for a role for markets in crime fighting, we conclude with a modest proposal. It might be useful to start a medium-scale prediction market, in which contracts are linked to the levels of various UCR crimes over the next three years. We would suggest recruiting traders from the broad community of criminologists and police chiefs across the nation, perhaps run under the auspices of an existing criminal justice umbrella organization, like the National Institute of Justice. We would suggest running small-scale real-money markets, and in order to stimulate trade (and ensure that relevant gambling laws are not breached), we would suggest that the market sponsor fund the account of each of the first 200 invited traders with an initial $200 grant, under the proviso that they can only withdraw funds after realizing $500 in turnover across their trades. We would also suggest an annual (non-financial) award for the top trader for each quarter, to further stimulate interest in and attention to the market. Setting up these markets is now a lot simpler than it was a decade ago, and there are vendors willing to provide software support for a web-mediated market for less than $10,000 per year.[111] In parallel with these markets, we would strongly suggest collecting real-time forecasts from competing methods, so as to provide a useful benchmark for assessing the accuracy of the market. Subsequent expansion in the range of contracts offered should be guided by the enthusiasm of traders, while an increasing role for these markets in the policy process can only be earned through collecting a track record of useful forecasts.

The lessons learned in terms of participation, contract design, and stakes needed to generate liquidity, not to mention the accuracy of the results, will be useful for other government entities that want to experiment with these markets. The federal role here would be similar to that already played by various federal agencies that are coordinating research and training in crime mapping and other analytical tools. Given the political battles that might be fought at the local level over rolling out a market like this, and given the overlapping federal, state, and local jurisdictions and agencies, we believe a federal experiment makes the most sense in the first instance. After a short while, however, given the uncertain issues we have just highlighted in this paper, much more experimentation at the state and local level will be needed. To that end, the federal government should encourage (or, at least, not discourage) the deployment of these markets. Although the science-fiction fantasy of predicting crime before it happens will likely remain just that, the use of markets in crime fighting policy has the potential to greatly improve the efficiency of the public safety response to crime.

111. Vendors like Consensus Point (http://www.consensuspoint.com/) provide turn-key markets and consulting for the operation of large and small online prediction markets.

APPENDIX: MODELING CRIME–MARKET–POLICY–CRIME FEEDBACK LOOP

The main text describes a very simple problem: changes in some underlying crime factor will have both a direct effect—raising the forecast level of crime—and a partly-offsetting indirect effect, as traders in prediction markets respond to the likelihood that policymakers will respond to this shock, lessening its influence. This Appendix formalizes some of the arguments made in the Article. Throughout, we use upper-case letters to denote endogenous variables, and lower-case letters to denote exogenous factors, while Greek letters refer to parameters (which are assumed common knowledge).[112]

Consider a simple case in which the crime rate, Y, is a function of some underlying level of criminality, x (itself likely an index of social, legal, economic and demographic factors), and some crime prevention measure, V. By re-scaling the variables x and V so that a one unit increase in each causes a one-unit change in crime, we are left with:

[1]

$$Y = x - V$$

When policymakers set the policy response V, they do so based on two imperfect forecasts of the underlying level of crime, x—a traditional forecast model and the forecast from a prediction market:

[2]

$$V = \beta \; Traditional\ forecast + \gamma \; Prediction\ market\ price$$

We impose no structure on the traditional forecast, but simply note that it comes with an orthogonal forecast error that we denote f:

[3]

$$Traditional\ forecast = x+f$$

The prediction market price, P, comes from an efficient market, and hence represents a statistically efficient forecast, given the market's information set. Thus, the prediction market price is simply the market's best estimate of crime, based on a noisy indicator of underlying criminality, $x+h$, where h is the noise term:[113]

[4]

$$P = E[Y \mid x+h]$$

At this point we have only laid out our assumptions, but already this basic setup highlights the feedback loop problem: Equation [4] shows that the prediction

112. We have also de-meaned all of the variables, allowing us to drop relevant constant terms.

113. We assume that the noise term, h is iid and orthogonal to x; we do allow h to be correlated with the equivalent noise term in the traditional forecast, f, and denote that correlation ρfh.

market price is a forecast of the crime rate, Y, but as equations [1] and [2] show, the crime rate is itself a function of crime prevention measures, V, which in turn are a function of the prediction market price.

Thus, prediction market prices, crime, and crime prevention, P, Y, and V are simultaneously determined. We can simply solve the system for these endogenous variables in order to uncover the true relationship between crime, prediction market prices and appropriate crime prevention measures.

In order to solve for the prediction market price, note that under the assumptions made on h, that an ordinary least squares regression will yield the best linear unbiased estimator of Y, and hence:

[5]

$$P = E[Y \mid x+h] = (x+h)\, E[(x+h)Y] \,/\, E[(x+h)^2]$$
$$= (x+h)\, E[(x+h)(X - \beta(x+f) - \gamma P)] \,/\, E[(x+h)^2]$$
$$= (x+h)\, \{(1-\beta)\, \sigma_x^2 - \beta\sigma_{fh} - \gamma\, E[(x+h)P]\,\} \,/\, (\sigma_x^2 + \sigma_h^2)$$

The feedback loop from policy to prices is evident in the two covariance terms, $\beta\sigma_{fh}$ and $\gamma E[(x+h)P]$. This latter term still involves the endogenous variable, P, We need to solve for the latter covariance term. Multiplying [5] by $(x+h)$ and taking expectations yields:

[6]

$$E[(x+h)\, P] = E[\, (x+h)\, (x+h)\, \{(1-\beta)\, \sigma_x^2 - \beta\sigma_{fh} - \gamma\, E[(x+h)\, P]\,\} \,/\, (\sigma_x^2 + \sigma_h^2)]$$
$$= [\, (1-\beta)\, \sigma_x^2 - \beta\sigma_{fh}\,] \,/\, (1 + \gamma)$$

Substituting this into the previous expression yields an expression for the prediction market price, purely in terms of exogenous variables:

[7]

$$P = E[Y|x+h] = (x+h)\, \{[\, (1-\beta)\, \sigma_x^2 - \beta\rho_{fh}\sigma_f\sigma_h\,] \,/\, (\sigma_x^2 + \sigma_h^2)\, (1+\gamma)\}$$

This expression allows us to find the relationship between prediction market prices and the information set of traders, $x+h$. The relationship between the two is linear, and the coefficient is the expression in curly braces.

This is actually a fairly intuitive expression, although it may be helpful to build the intuition step-by-step, by beginning with the simplest case.

In the simplest (but clearly unrealistic) case, the market observes the underlying index of criminality, x, perfectly (and hence $\sigma_h=0$), and policy is unresponsive to both types of forecast ($\beta=\gamma=0$). In this case, the prediction market price simply moves one-for-one with $(x+h)$. We do not live in this world though, so this model builds in several factors that make its prediction more realistic.

First, we allow for the fact that market participants do not observe criminality perfectly, but instead observe $x+h$, (and hence $\sigma_h>0$). This leads the prediction market forecast to move with this noisy indicator, scaled by the signal-to-noise ratio $\sigma_x^2/(\sigma_x^2 + \sigma_h^2)$. This result is familiar, as it is the standard finding that an efficient ordinary least squares (OLS) estimator in the presence of measurement error requires attenuated forecasts.

Second, we allow for the possibility that policy responds to the traditional forecast ($\beta>0$). This response, designated β, means that any crime shocks will be further reduced to a remaining factor $(1-\beta)$, and this endogenous response is understood by prediction market traders. That is, $P = (x+h)\,(1-\beta)\,\sigma_x^2 / (\sigma_x^2 + \sigma_h^2)$, and hence the response of the prediction market forecast to a rise in underlying crime is further muted by the expected response of policy to offset this expected rise in crime. If policy fully offsets any shocks to crime ($\beta=1$), then the crime rate will be orthogonal to shocks to the underlying crime factor, and hence the prediction market price provides no information about the underlying crime factor, x. If shocks are less than fully offset ($0<\beta<1$), then the prediction market price provides useful, albeit attenuated assessments of the underlying crime.

Third, in a world with crime prediction markets, policymakers also will likely respond (somewhat) to the prediction market prices. In the model, this response is designated by an amount γ. In turn, this endogenous response to a rise in criminality (x) will lead to a smaller impact on crime, attenuating the ultimate impact by $1/(1+\gamma)$. Since prediction market traders are aware of this feedback loop and the relationship between the prediction market price and x will be similarly attenuated, the market should do the same. An important finding of this model is that as long as the policymaker does not respond infinitely strongly to prediction market prices (that is, $\gamma<\infty$), there will still be a positive (albeit attenuated) relationship between the prediction market price and the underlying crime factor.[114] This means that prediction market prices are still valuable for policymakers in all conceivable cases, even when reactions to underlying crime factors are wildly overaggressive.

Fourth, we allow for the possibility that the traditional forecast and the prediction market forecast are not independent, and hence the errors in projecting the underlying index of criminality, x, are correlated. Consequently some of the prediction market forecast error will be common to the traditional forecast, and hence policy is already partly offset by the response to the traditional forecast. This is the (rough) intuition for the $-\beta\rho_{fh}\sigma_f\sigma_h$ term.

Finally, now that we have an expression for the prediction market price in terms of the exogenous variables, we can solve for the crime rate and crime-reducing measures:

$$Y = x-V = x - \beta(x+f) - \gamma(x+h)\,[\,(1-\beta)\,\sigma_x^2 - \beta\rho_{fh}\sigma_f\sigma_h\,] / (\sigma_x^2 + \sigma_h^2)(1+\gamma)$$

$$= x(1 - \beta - \theta\gamma) - \beta f - \gamma\theta h \quad \text{where } \theta = [\,(1-\beta)\,\sigma_x^2 - \beta\rho_{fh}\sigma_f\sigma_h\,] / (\sigma_x^2 + \sigma_h^2)(1+\gamma)$$

114. The intuition for why the limit here is here is $\gamma=\infty$ is that the more that policymakers work to offset the rise in crime signaled by prediction market prices, the less that prediction market prices respond to the underlying crime factor.

Thus, crime rises with the underlying rate of criminality, x, but this affect is partly offset by the response of policy to the traditional forecast (by an amount β), and partly offset by the response of policy to the prediction market forecast. Of course, forecast errors in either model will also have an impact on crime: an excessively high crime forecast leads to the deployment of extra crime-fighting resources, which results in a lower crime rate than if the forecast error had not occurred.