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Predicting Crime

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Abstract

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 paper proposes and examinesthe use of prediction markets to forecast crime rates and the impact on crime from changes to crime policy, such as resource allocation, policing strategies, sentencing, post-conviction treatment, and so on. We make several contributions to the prediction markets and crime forecasting literature.

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 policy-making applications, such as crime rate forecasting. Specifically, we 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. Given the high costs of changing policies, say issuing a moratorium on the death penalty or lowering mandatory minimum sentences for certain crimes, these markets provide a useful tool for policy makers operating under uncertainty.

These event studies and the other policy markets we propose face a big hurdle, however, because predictions about the future imbed assumptions about the very policy choices they are designed to measure. We offer a method by which policy makers 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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According to science fiction author Philip K. Dick, in fifty years or so our society will have the ability to predict certain crimes before they happen.[1] Policy makers today, however, do not have certain knowledge of future events, say what the crime rate will be in Chicago in the next hour, next year, or next decade, so they have to resort to various more imprecise forecasting tools. These include gut feeling, what was done in the past, and modeling based on maps overlaid with past crimes and things like the location of liquor stores or demographic data. Policy makers extrapolate from past events, as they must, but do so in a manner that is not systematic, transparent, nor 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 this goal. There are several potential reasons for this failure that come to mind.

The first reason is that 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, occasionally difficult to interpret, and occasionally 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,

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[1] *See* PHILIP K. DICK, MINORITY REPORT (2002). The short story was made into a popular 2002 movie directed by Steve Spielberg. *See* http://www.imdb.com/title/tt0181689/.

[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 A.M. Olligschlaeger, *Artificial Neural Networks and Crime Mapping*, in D. Weisburd and T. McEwen, eds., CRIME MAPPING, CRIME PREVENTION, CRIME PREVENTION STUDIES 8 (1998).

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.

We contribute a new forecasting tool—crime forecasting prediction markets—that may be more affordable, accessible, and accurate for the relevant decision makers. 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.

The paper 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 decision makers 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 policy makers to interpret market prices even when the prices include imbedded predictions about future policy changes and (2) allow policy makers to estimate the causal impact of hypothetical policy changes on crime rates.

A second and related reason why technical and systematic forecasting may be unobserved is because it takes place in an informal, tradition-based manner inside of the minds of key decision makers. The practice of forecasting is as old as crime regulation and policing, since all policy makers, from the governor to local police chiefs, must make

[4] For example, FacilityCop, a software-forecasting tool developed at Temple University, is available as a free download. *See* http://www.temple.edu/cj/faccop/.

decisions about how to allocate scarce resources.[5] In the absence of specific forecasting tools, the most likely method of predicting crime is human-based pattern recognition and the gut instincts of decision makers. In other words, police chiefs have a feeling about where crimes will occur or the governor has a prior about crime patterns or the impact of tools like the death penalty or parole, and these are used to make policy decisions.

This kind of decisionmaking may be successful in some instances given experienced decision makers and some ex post political accountability checks, but undoubtedly these techniques will be crude, subject to political biases, and possibly systematically skewed by decisionmaking heuristics and errors by well-meaning decision makers. 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, perhaps dramatically, the opportunities for policy makers 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, say, 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; decision makers too 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

[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 decisionmaking, extracted largely from work in psychology, sociology, and economics, are described in detail in the legal literature. *See, for example,* CASS R. SUNSTEIN, ED., BEHAVIORAL LAW & ECONOMICS (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 it has the ability to change long-standing practices in the same way that Beane's application of Sabremetrics did for baseball.

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are failing despite (or because of) city efforts; the whole concept of betting on crime might be normatively troubling to some citizens; and so on. We highlight these problems and offer some initial thoughts on solutions, proposing a simple first step in the direction of more robust markets for predicting crime.

The paper is organized as follows. Part I of the paper describes the basic theoretical underpinnings of prediction markets. These markets are fairly well understood, but we contribute 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 policy makers 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. As we show below, policy makers may be able to "delegate" crime policy to the market by establishing a rough algorithm of policy responses to future events, and then asking the market to predict the future events in light of this rule. This delegation seems to be implicitly going on to some extent in macroeconomic policy,[8] and we argue that it may make sense here as well.

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 policy makers 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

[8] *See* note __ and surrounding text.

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 V concludes with a modest proposal and some open questions.

I. Forecasting and Prediction Markets

A. The Forecasting Problem

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.[9] These include the fact that 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; decisionmaking heuristics and barriers to information flow to key decision makers may inhibit analysis; 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—have been used in each of these cases.[10]

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

[9] Benign but disruptive factors include various decisionmaking 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, s*ee* Michael Abramowicz and M. Todd Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. 1343, 1384-85 (2007) (concluding that concerns are overblown), and we discuss it briefly in Part IV below.

[10] *See*, *generally*, Justin Wolfers and Eric Zitzewitz, *Prediction Markets*, 18 J. ECON. PERSPECT. 107 (2004) (describing existing prediction markets and their general application); Abramowicz and Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. at 1349-50, *supra* note __ (describing markets at Hewlett-Packard used to more accurately predict printer sales than existing methods).

printers will be sold in the next quarter, who will win the next presidential election, or what the number of homicides in Chicago will be in the next year.[11]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 percent likely) that the number of burglaries will rise. If an array of 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".[12] If the market is fairly efficient,[13] we can be pretty sure 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.[14]

Of course, there are many reasons to be concerned that prediction markets, like all markets, are not perfectly efficient. As such, the usefulness of prediction markets for crime rate forecasting purposes (or any other forecasting purposes) is an empirical question. The policy-relevant question is not "Are prediction markets accurate predictors of crime rates?" but rather: "Do prediction markets yield more accurate crime rate forecasts than alternative approaches?" While to our knowledge crime-forecasting

[11] *See, for example,* Wolfers and Zitzewitz, *Prediction Markets*, 18 J. ECON. PERSPECT. at 110 (describing existing prediction markets and their general application); Abramowicz and Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. at 1349-50, *supra* note __ (same).

[12] *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 SUNSTEIN, INFOTOPIA (2006).

[13] 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 (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, say on criminal, demographic, economic or other trends, can be used to improve on the market-generated forecasts.

[14] 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 $1.00 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.

prediction markets have never been run, 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:

> In fact, in every known head to head field comparison between speculative markets and other social institutions that forecast, the markets have been no less, and usually more, accurate. 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 he and others detail at length the theoretical and practical reasons for these results.[16] The Condercet Jury Theorem is one reason, since it shows that, under certain reasonable assumptions, as the number of individuals participating in a decision increases, the probability of reaching the correct result increases dramatically.

Prediction markets allow any and all voices to be heard, inducing a movement towards better forecast estimates. In addition, Sunstein shows how, in the absence of market mechanisms, mental heuristics inhibit information flow to decision makers, how point estimates by experts or decisionmaking groups are less reliable than the smoothed aggregations of everyone's opinion, and how even the most well designed and well informed groups of experts cannot in general match the power of market-based information aggregators.

These markets work because they have several key factors relevant to accurate forecasting. First, they aggregate information from any and all persons holding valuable information, regardless of who they are, what their social status is, where they fit in a

[15] Robin Hanson, Foul Play in Information Markets, in ROBERT HAHN AND PAUL TETLOCK, EDS., INFORMATION MARKETS: A NEW WAY OF MAKING DECISIONS 126 (2006).
[16] SUNSTEIN, INFOTOPIA at 117, *supra* note __.

decisionmaking hierarchy, or what their information is based on.[17] 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 simply debiasing 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. This might be especially important in crime policy, since many believe that a major impediment to the flow of information to police and other decision makers 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 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]

Second, these markets provide a financial incentive to disclose information. Academics, neighbors, and public safety officials may all have relevant information, but might 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 very low and are shared with many 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

[17] *See id.*

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

[19] Although aggregation of dispersed information is something that might benefit many areas of public policy decisionmaking, the case is easiest in crime rate forecasting. The fact that information may be disproportionately located in individuals or places outside of the official decisionmaking 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; and so on. 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 bureaucratic red tape. Or the information may be shared but in a way that is not believable, 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 here given the multiple jurisdictions and agendas at play in public safety enforcement. Markets are especially powerful in reducing these types of transaction and coordination costs.

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]

Third, and closely related to the financial incentive, is that markets allow forecasts to be weighted according 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" by 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 does not. In addition, an expert's $100 bet is, *ceteris paribus*, more reliable than her $1 bet on the same issue. 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 know these things better, the ability to give weight to their own contribution. This is especially important if one believes, as we do, that in the crime prediction business, recipients are likely to be systematically biased or incapable of 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 your Aunt Mary, has information that might be relevant to how many burglaries there will be on Chicago's North Side next week or next year, 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 won't carry much weight unless it gives authorities specific information about past events or very likely future events. Many tipsters are dismissed as crackpots. Police are also inundated with tips of all kinds, real, fake, and self-serving, and both unsubstantiated hunches and complicated computer

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[21] *See* Emile Servan-Schreiber, et al., *Prediction Markets: Does Money Matter?*, 14 ELECTRONIC MARKETS 3 (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, INFOTOPIA at 117, *supra* note __ (describing markets at Microsoft, Google, and other firms, using things like lottery tickets for Xbox game consols).

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, bandwidth of officials, and so on exist here too. In addition, Aunt Mary, who might have information of equal or better quality than the expert, is unlikely to get the eyes or ears of key decision makers. She might not even know with whom to speak.

A public prediction market, however, solves all these problems. Anyone with information, big or small, highly confident or a hunch, can go to a centralized (virtual) location and place a confidence-weighted bet on the future. Policy makers enjoy a benefit too, since they can look to one particular location, say 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 decision makers, such as the governor of a state. At present, decision makers 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 and hidden ways.[24] With a prediction market, the cacophony of forecasts are reduced to a single estimate that the policy maker 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.

[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.

[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, MISMEASURE OF CRIME at 34, *supra* note __. 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 and Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. at __, *supra* note __.

Finally, markets provide instantaneous and continuous feedback to information providers through prices. This does two things. For one, 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). For another, 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 criminology expert sees the market price/forecast for crime to fall next year in Chicago, but her model shows 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 the 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 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, potential litigation, and so on.[28] Some

[26] *See* Joyce Berg, et al., *Results from a Dozen Years of Election Futures Markets Research*, in CHARLES R. PLOTT AND VERNON L. SMITH, EDS., THE HANDBOOK OF EXPERIMENTAL ECONOMICS RESULTS (2003).

[27] Intrade (www.intrade.com), for example, runs prediction markets on current events, financial topics, politics, and the weather. Betfair (www.betfair.com) is similar.

[28] *See* Abramowicz and Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. at 1349-50, *supra* note __ (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 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, INFOTOPIA at 122, *supra* note __.

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 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 geography.[30] It seems inevitable that these markets would eventually find their way from serving as inputs for private actors to data for government policy makers.

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 authority, more often than not government officials' decisions fail to fully take into account the results of this analysis. Prices in markets are immediate and transparent, and this reduces processing costs, including time. Indeed, 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 frequently public officials are presented with information that is significantly out of date.

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

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[29] Refet S. Gurkaynak and Justin Wolfers, "Macroeconomic Derivatives: An Initial Analysis of Market-Based Macro Forecasts, Uncertainty and Risk" (January 2006). CEPR Discussion Paper No. 5466 Available at SSRN: http://ssrn.com/abstract=900392.

[30] *See* http://www.cme.com/trading/.

[31] *See, for example,* Robert Looney, *DARPA's Policy Analysis Market for Intelligence: Outside the Box or Off the Wall?*, 9 STRATEGIC INSIGHTS __ (2003), available at http://www.ccc.nps.navy.mil/si/sept03/terrorism.asp.

[32] *See* MICHAEL ABRAMOWICZ, PREDICTOCRACY __ (2008); *see also*, Andrew Leigh, et al., "What Do Financial Markets Think of War in Iraq?", Stanford GSB Research Paper No. 1785, available at SSRN: http://ssrn.com/abstract=388762 (Mar. 18, 2003).

[33] Center for Disease Control and Prevention http://www3.niaid.nih.gov/healthscience/healthtopics/Flu/aboutFlu/DefinitionsOverview.htm

[34] National Center for Biotechnology Information http://www.ncbi.nlm.nih.gov/sites/entrez?cmd=Retrieve&db=PubMed&list_uids=3109239&dopt=AbstractPlus.

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 don't. The incentives are very high for predictions about the flu to be made by individuals with information about trends, but until recently the only forecasting being done, if any, was that of individual doctors or policy makers 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. 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 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.[35] 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 percent of observations predicted the correct color, and 100 percent of observations were one color or less away from the correct prediction level. As one would expect, forecasts improved

[35] *See* Philip M. Polgreen, et al., *Use of Prediction Markets to Forecast Infectious Disease Activity*, HEALTHCARE EPIDEMIOLOGY, January 2007.

closer to the relevant measurement period: one week before, the markets predicted the correct color about 70 percent of the time on average. These results are far superior to any other mechanism used anywhere by anyone.

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 to more accurate and timely forecasts may be substantial.[36] Before turning to how prediction market data can be used to inform policymaking, we will set the stage by describing the current methods used by policy makers.

C. 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 in determining the amount of crime fighting resources needed and how they should be allocated across the jurisdiction. Our review of current practices reveals that there is an abundance of tools and methods for forecasting, but these are rarely if ever used. And, in any event, they are unlikely to be as effective as those we suggest in this paper.

[36] 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 in way.

i. Academic Models

Substantial scholarship exists within the field of criminology discussing methods of forecasting future trends in criminal activity. Existing prediction mechanisms, however, tend to focus on extrapolating from data collected on past crimes, rather than attempting to aggregate information from crime professionals on estimates of future developments. To be sure, the past can be used to help predict the future, but the existing methods for doing this are not commonly used, let alone systematic or theoretically sound. And, at the least, the dangers of idiosyncratic and potentially biased mechanisms of *individuals* extrapolating from past experience on their own should be obvious.

There are some relatively new forecasting models related to crime trends. These models use multiple-regression analysis to determine the statistical significance of different factors in determining the crime rate. A pioneer in this field is James Alan Fox who, in his book *Forecasting Crime Data*, attempts to predict future crime trends using a range of variables, including violent crime rate, property crime rate, size of police force, police force expenditure, unemployment rate, consumer price index, and estimates of the resident population by race and by age.[37] The models are complex and the results ambiguous.

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-land area.[38] The predictive accuracy of their model varied widely depending on the type of crime in question. For example, rates of larceny/theft were by far the most predictable, with the number of offenses in eleven cities predicted within 10 percent for the year 1982. In contrast, only three out of the fourteen cities in which burglary was studied produced an accurate prediction, and predictive success for aggravated assault varied widely, from very accurate predictions to completely unpredictable, depending on the city in question. 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 give jurisdiction.

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[37] James Alan Fox, *Forecasting Crime Data*, 70 J. CRIM. L. AND CRIMINOLOGY 273 (1979).

[38] Caroline Rebecca Block and Sheryl L. Knight, "Is Crime Predictable?" Illinois Criminal Justice Information Authority, 1987.

Perhaps the most successful experiment to date that we are aware of comes from a study in Britain that reran 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, occur in neighboring areas over short periods. Kate Bowers, Shane Johnson, and Ken Pease compared three methods for predicting burglaries in and around Liverpool, England.[39]

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

The second, called "retrospective hot spotting", is the most widely accepted method among academic criminologists.[40] This 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. This technique differs from the final one, called "prospective hot spotting", only in that it does not weight 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 the authors were studying) tend to be highly localized in time and space, and are thus "communicable".[41] 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 rerunning history using historical data. They found that had their approach been used, they would have predicted 62 percent of burglaries within two days, compared with 46 percent for the retrospective technique, and only 12 percent for the beat technique. Despite these robust findings, we know of no police force that actively uses this modeling approach. In

[39] Kate J. Bowers, et al., *The Future of Crime Mapping*, 44 BRITISH J. CRIMINOLOGY 641 (2004).

[40] *See* J. Ratcliffe, *Aoristic Analysis: The Spatial Interpretation of Unspecific Temporal Events*, 14 J. GEOGRAPHIC INFO. SCIENCE 669 (2000).

[41] The authors show that "the risk of victimization increase[es] 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., *Future of Crime Mapping*, 44 BRITISH J. CRIMINOLOGY at 3, *supra* note __.

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 may yield biased estimates due to manipulation, user error, or other factors. For example, burglars might adapt their behavior to foil the model. The possibility of using this or other techniques as inputs to a market-based assessment would be superior in light of this possibility.

ii. 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.[42] 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 about crimes that occur. Decision makers then can populate crime maps with demographic data, locations of points of interest, like police stations, schools, bars, and so on, as well as any other information that users might think is relevant to crime prediction.[43]

The process of forecasting and evaluation in this context is less technical than managerial, as its use by the NYPD and departments in other cities[44] is primarily about framing data and issues for analysis and discussion, instead of 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 cases, crime patterns and police activities. This data, which includes the

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

[43] The theoretical underpinnings are based work in environmental criminology, s*ee, for example,* PATRICIA BRANTINGHAM AND PAUL BRANTINGHAM (EDS), ENVIRONMENTAL CRIMINOLOGY (1981), routine activity theory, *see* Lawrence Cohen and Marcus Felson, *Social change and crime rate trends: A routine activity approach,* 44 AM. SOC. REV. 588 (1979).

[44] This approach is in use in Los Angeles, Philadelphia, and Baltimore.

> 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 bycomputer 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.[45]

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 decisionmaking.

Accordingly, the process is extremely localized and subject to the idiosyncrasies 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 decision makers think is relevant. Although we are not aware of any systematic data on the success of these mapping systems, their usefulness is limited by 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. There are, to be sure, very new federal programs designed to develop standards and provide training in this area, but the diversity of models, agencies, and techniques makes for large practical hurdles for policy makers interested in deploying the best available forecasting means[b1].

The federal government has invested some resources to try and overcome barriers to implementing existing forecasting tools. The most obvious consequence of this investment is a series of conferences at which academics and public safety officials share

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

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data.[46][b2] The bounty of these conferences is promising but reinforces our earlier 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,[47] but it is clear that the information is not being aggregated.[48] It also shows the challenge that any decision maker 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.[49]

Despite the significant research on the subject in the past fifty years, no widely accepted method for predicting criminal activity has emerged. As with the influenza statistics, the publication of information that is timely, accurate, and in a format that can be understood and used by law enforcement personnel working on the ground level remains a formidable task. Indeed, because the task of transforming much of

[46] For example, the National Law Enforcement and 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." The Center's Crime Mapping and Analysis Program provides technical assistance and training "in the areas of crime and intelligence analysis and geographic information systems." *See* http://www.ojp.usdoj.gov/nij/maps/. 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, for example,* the International Association of Crime Analysts (available at www.iaca.net); http://www.crimeanalysts.net/. 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 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.

[47] 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 policy makers is dispersed and siloed in inefficient ways.

[48] A variety of public-facing tools for citizens and policy makers are also available through web-based mapping programs. There are web sites 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 web sites suggest several interesting conclusions. For one, there already exists lots 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. This data and these web sites 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 web sites also show that there is a demand for this data among the general public, who will be vital to creating a liquid market that will produce interesting results. The overabundance of sources is also evident, as numerous providers are available, not all of which have complete data or coverage. For example, one of the authors tried to use the 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.

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

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criminological research from an academic exercise to actionable information presents a difficult obstacle, many decisions taken by professionals are based on "gut instinct" rather than fact-based analysis. This is confirmed by our discussions with policy makers at all levels.

With this abundance of data and shortcoming of analysis and thinking as background, we turn to our contribution to this field.

II. Prediction Market Forecasts for Crime and Crime Policy

A. Basics Crime Forecasting

Crime forecasting research has been largely academic, and consists almost entirely of mapping and modeling historical data to geographies, 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 above, of only very limited use. Moreover, it is clear from discussions with crime prevention decision makers that these techniques aren't being systematically used on the ground to make predictions either about localized crime trends (for example, what the crime will be in a particular area of the city in the next two weeks) or 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, aren't using them either.

Very simple markets can be designed for either purpose, 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 policy maker, say one setting sentencing policy or allocating budget for future prosecutorial and prison functions, wanted to determine the best estimate of the violent crime rate in a particular geography for a future year. The policy maker could float a contract that pays \$1 if the violent crime rate in the year in question is between 20 and 25 victimizations per thousand people (and \$0 otherwise).[50] The market could also include other potential ranges, such as 10-15, 15-20, 25-30, 35-40 and so on, with similar payoffs. Specifying the entire range of probably outcomes has the advantage that the market not only reveals an expected future crime rate, but also a

[50] Since the bet is effectively \$1 or \$0, these contracts are called "binary options."

complete probability distribution. This would allow the policy maker to determine the most likely outcome, the 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 in a year 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 30-35 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 percent 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 30-35 range, while simultaneously buying contracts in the 10-15 range, which is what his gut tells him is the right answer.[51] 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.

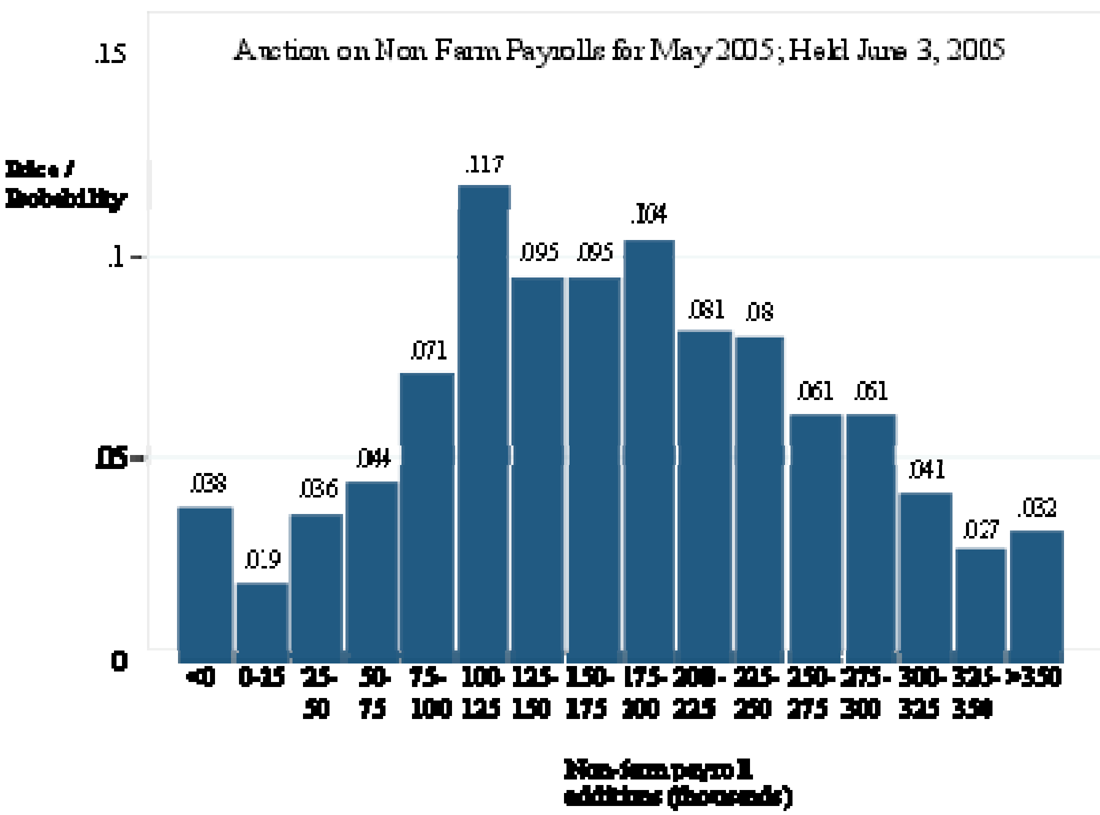
Not only are the prediction market estimates an improvement in terms of forecasting, they also add a useful probability dimension to any forecast. As noted above, using a range of potential future outcomes as contract reference points allows policy makers not only to assess the most likely outcome, but also permits policy makers to

[51] 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 discussed elsewhere in a related context. *See* Abramowicz and Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. at 1349-50, *supra* note __ . 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* Refet S. Gurkaynak and Justin Wolfers, "Macroeconomic Derivatives: An Initial Analysis of Market-Based Macro Forecasts, Uncertainty and Risk," IZA Discussion Paper No. 1899 (January 2006), available at SSRN: http://ssrn.com/abstract=875413.

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 will 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 percent 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 percent confidence interval extending from 0 to 350,000 jobs.

Figure 1



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

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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 policy makers. 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, so we will discuss only those issues that are particularly relevant when considering the role of market-generated forecasts.

i. **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 analyses 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.[52] This report tells us, for instance, that there were 25,314 burglaries in the City of Chicago in 2005.[53] The report for 2006 will not be issued until September 2007, however, making the data less useful for policy makers 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, say, some decisions for the current or next yearto 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.[54]

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[52] *See* http://www.fbi.gov/ucr/ucr.htm.

[53] *See* http://www.fbi.gov/ucr/05cius/data/table_08_il.html.

[54] 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 and Kenneth N. Fortson, *Do Markets Respond More to More Reliable Labor Market Data? A Test of Market Rationality*, 1 J. EUROPEAN ECON. ASSOC.,931 (2003).

ii. **Simple Forecasts of the Future**

Since we assume that the maximand for policy makers is crime reduction, and the only short-term lever for implementation is the number of police officers to allocate to a particular area, a more ambitious program might involve the use of a forward-looking prediction market for informing resource allocation decisions. 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. The market will give an estimate, through a price, of the future crime rate that is likely to be better than any individual or group's estimate of the same rate.

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 tradersto 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, if policing levels respond sufficiently strongly to prediction market prices, then in equilibrium market participants understand that policymakers are working to ensure that no area sees disproportionately high crime, and hence the market will predict equal crime rates in all areas of the city—regardless of the evolution of the underlying factors influencing 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 (unbiased and statistically) forecasts. Rather, the subtle issue considered here relates to how forecasts might serve as an input to the policy process.[55]

[55] 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.

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—*certaincrime rates conditional on current policing patterns persisting*—this forecast reveals a confluence of underlying crime factors and the policy reaction function.[56] 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 (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 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

[56] The difficulty here is quite familiar in the economic context, as forecasts of interest rates by both bond markets and professional 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." *See* http://gregmankiw.blogspot.com/2006/07/how-to-decentralize-monetary-policy.html.

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 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 policy makers 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 be orthogonal to 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 policy makers 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 policy maker 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 policy makers, 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)

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policymakers respond to rises in 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 markets 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 percent, markets may expect the policymaker to respond by raising the police presence sufficiently to partly offset this. As such, the prediction market may only suggest that the number of burglaries in the North of the city will be higher by 3 percent. 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, policy makers should be aware of this feedback loop, and should respond to this forecast of a 3 percent higher burglary rate *as if* it is forecasting 10 percent higher burglary rate, and respond accordingly. If the policymaker responds to the degree anticipated, then the number of burglaries will rise by only 3 percent, despite the fact that underlying factors shifted enough to raise burglaries by 10 percent.

So long as the market knows with some certainty the likely reaction of policy makers, this can lead the market to an efficient estimate of crime rates, since traders can incorporate the reaction into their forecasts, and policy makers can unpack forecasts and expected policy responses when setting policy. This all sounds circular, but it can be solved fairly easily as we discussed above. 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; and so on. The result is an equilibrium in which market forecasts help inform policy makers about appropriate resource allocations.

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C. Using Markets to InformPolicy

The most important questions for crime policy, and ones that the simple prediction markets discussed above are not designed to address, are about the efficacy of different types of crime-reduction interventions. The policy-relevant questions are whether to devote greater resources to police on the street, or to incarceration; whether to focus efforts on social programs, or in 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 refer to as *prediction market event studies* and the second involves *contingent prediction markets*.[57]

i. 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 the firm decides to purchase a competitor, and if the announcement of this decision is accompanied by an increase in its stock price, it is likely that the market believes that this policy decision 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, with this price representing the market-based probability of that particular outcome. Given this market, one could perform a prediction-market event study, looking to see

[57] *See* Joel Slemrod and Timothy Greimel, *Did Steve Forbes Scare the U.S. Municipal Bond Market?* 74 J. PUBLIC ECON. 81 (1999) (examining impact of Forbes's 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 QUART. J. ECON. 807 (2007) (using prediction market event study to examine the effect of election results on economic variables); Wolfers and Zitzewitz (2004) discusses results from markets designed to predict the effect of political and economic events on the 2004 Presidential election, and Wolfers and Zitzewitz (2006) discuss distinguishing correlation from causality.

ifthe announcement of, say, a death penalty moratorium led the market to forecast higher or lower homicide rates.[58]

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.[59] 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 both inconsistent and widely different.[60]

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 thatthe market may have factored into the pre-announcement market price some probability that the event to be tested would occur.[61] So, if a prediction market is running on the issue of future

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[58] 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.

[59] *See, for example,* H. Dezhbakhsh, et al., *Does Capital Punishment Have a Deterrent Effect? New Evidence from Postmoratorium Panel Data*, 5 AM. LAW ECON. REV. 344 (2003); Isaac Ehrlich, *The Deterrent Effect of Capital Punishment: A Question of Life and Death*, 65 AM. ECON. REV. 397 (1975).

[60] *Compare* Cass R. Sunstein and Adrian Vermeule, *Is Capital Punishment Morally Required?*, 58 STAN. L. REV. 706 (2005); *with* John Donohue and Justin Wolfers, *Uses and Abuses of Statistical Evidence in the Death Penalty Debate*, 58 STAN. L. REV. 706 (2005).

[61] For an interesting technical analysis of a related issue, *see* Anup Malani, "Accounting for Expectations of Law" University of Chicago Law and Economics Working Paper, 2008, available at ________.

homicide rates in Illinois, and Illinois announces a moratorium on capital punishment, there might not be changes in the homicide market if the market already "knew" that the moratorium was going to be implemented.[62] In the limit, if the market was already certain that the Illinois governor was going to issue a death penalty moratorium, then the announcement of the decision would have no effect at all on crime prediction market prices, which 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 percent 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).[63] Thus, if the announcement of a moratorium led the markets to revise upward (downward) its homicide forecast by 10 percent and the market assessment of a moratorium rose 70 percent, we can infer the market believes the impact of the moratorium on homicides would be an increase (decrease) in homicides of 14 percent. The ability to isolate such causal parameters through multiple markets is a key advantage of prediction markets.

[62] 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

[63] 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.

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Another advantage of prediction market event studies over observational econometric event studies is the ability to 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 that would raise the likelihood of a death penalty moratorium being implemented, also raises the likelihood of more restrictions on the use of particular investigative tactics or force by police. If so, then crime prediction markets may respond to change in the likelihood of both of these policies, leading the event study approach to confound the effects of executions and the effect 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 the set of issues that one can study is confined to issues which there are useful "events" or "policy shocks". In the next sub-Part, however, we address a potential solution that can overcome this limitation.

ii. **Simple Contingent Markets**

In a contingent market, individuals trade contracts whose payoffs are linked to *both* the likelihood of a policy change and to subsequent levels of crime. Using contingent markets, we can, with some very simple math, determine the expected impact of a particular policy choice on crime. Continuing with the example above, let's say that the governor of Illinois is considering a death penalty moratorium, and she wants to know what best estimate of the impact of this policy choice would be on homicide rates. The governor (or more likely her aides) could review the vast literature on this subject, counting studies for and against, perhaps weighted by the fame of their authors or the

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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. These methods are, however, clearly inferior to the market design we postulate 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 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 the staff or the commission, are inferior to market-based mechanisms because of the potential for polarization, for hidden profiles (i.e., individuals with information may not reveal it for social or psychological reasons), to keep information private, and other factors.[64] Markets also allow constant deliberation. 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. Finally, 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 improves transparency of the policy deliberation process in a way that does not undermine the potential to reach a positive result is a good thing.[65]

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:

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;

[64] *See* SUNSTEIN, INFOTOPIA at 65, *supra* note __.

[65] 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 (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* Association of American Physicians and Surgeons, Inc. v. Hillary Rodham Clinton, 997 F.2d 898 (D.C. Cir. 1993) (ruling in case challenging openness of proceedings).

c) There is no death penalty moratorium, and homicide rates are higher than today; and
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 web site, thereby allowing the public to have a continual window into the "market's" view on the question. A benefit of this transparency would be political accountability—a politician that opted to ignore the market would likely have to build a strong case for their position.

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 lower with a death penalty. From the four securities, these probabilities are:

Probability (Homicide is lower | No death penalty) = b/(a+b); and

Probability(Homicide is lower |Death penalty) = d/(c+d).

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: if the price of security (a) (moratorium and higher homicide rates) is \$0.60; the price of security (b) (moratorium and lower) is \$0.20; the price of security (c) (no moratorium and higher) is \$0.30; and the price of security (d) (no moratorium and lower) is \$0.70, we can conclude the probability of a reduction in homicides with a death penalty moratorium is 25 percent, and the probability of a reduction in homicides with the death penalty is 70 percent. This would suggest that *the market believes* there is a strong deterrent effect from the death penalty.

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iii. **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, say, 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, the use of capital punishment, and so on.

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 contract 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.[66]The difference between the price of these prediction market contracts (at any time) reveals the extent to which the market believes a higher or lower homicide count can be expected in those states of nature in which a death penalty moratorium occurs.[67]

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.[68] Other market designs can help policy makers understand the uncertainty surrounding the market's

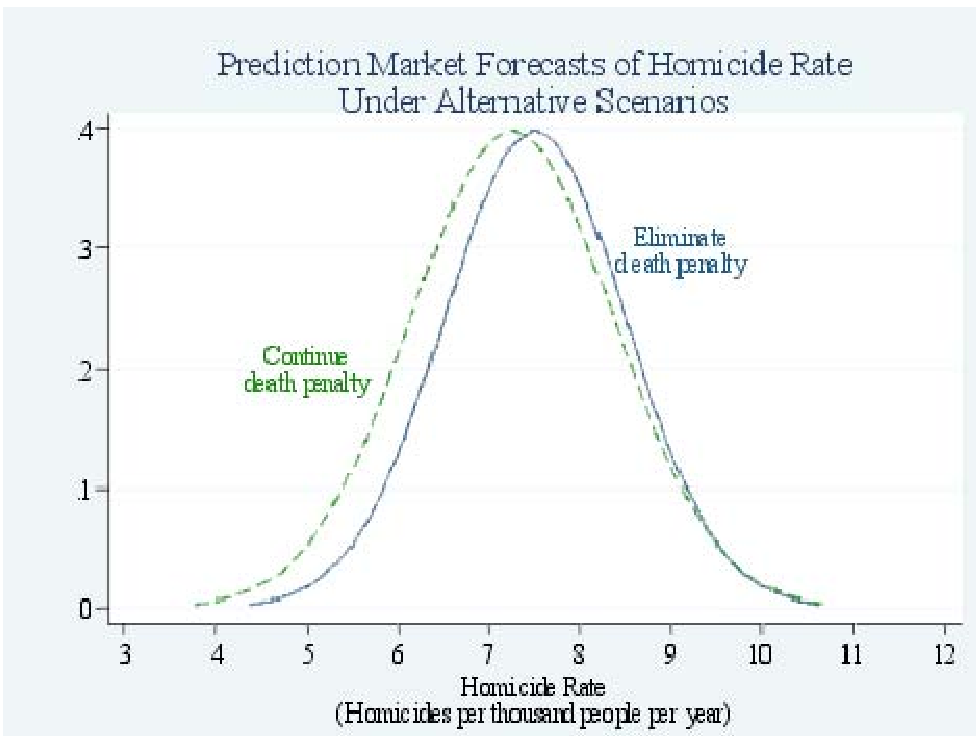
[66] In simple notation: (*E[Homicides | Death penalty]*); and (*E[Homicides | Death penalty moratorium]*).

[67] 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 percent 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.

[68] Or, more fully, the precision of the market's conditional expectations.

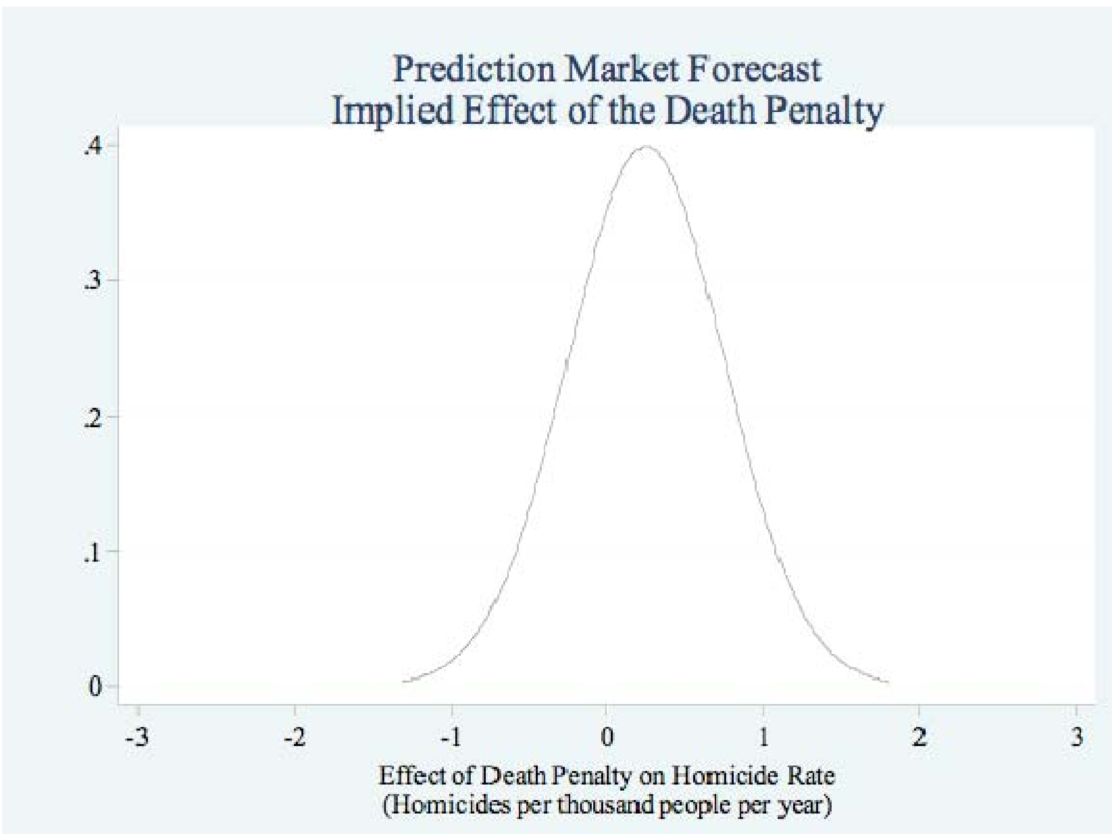
estimate. Consider an alternative design: a prediction market is created with a series of contracts that pay $1 if a trader accurately predicts *both* the homicide rate and whether Illinois has the death penalty. For instance, one example would be a contract paying $1 if Illinois has the death penalty 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.

Figure 2



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)*. A similar distribution, denoted f(h,0), for the no-death-penalty scenario is shown in the next panel. 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.[69] This is shown on Figure 3.

Figure 3



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

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

year after a moratorium or abolition.[70] A leading study uses this approach and concludes that each additional execution decreases homicides by about five. Another study by Dezhbakhsh, Rubin, and Shepherd used a system of simultaneous equations and county-level panel data that covered 3,054 counties for the 1977-96 period.[71] 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 explore then effects on the crime rate. They found that each execution prevents about 18 homicides on average.[72] Other, more recent studies, find some ambiguity in the data on homicide rate averages, concluding that the "the existing evidence for deterrence is surprisingly fragile, and even small changes in specifications yield dramatically different results."[73] They 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."[74] 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 policy makers. 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 a police chief to actually reallocate resources to

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[70] *See* Hashem Dezhbakhsh and Joanna M. Shepherd, *The Deterrent Effect of Capital Punishment: Evidence from a "Judicial Experiment",* tbls.3 and 4 (Am. Law & Econ. Ass'n Working Paper No. 18, 2004), available at http://law.bepress.com/cgi/viewcontent.cgi?article=1017&context=alea (last visited Dec. 4, 2005) (using data from 1960-2000).

[71] *See* Dezhbakhsh, et al, *Does Capital Punishment Have a Deterrent Effect?* 5 AM. L. & ECON. REV. at __, *supra* note __.

[72] *See* id.

[73] Donohue and Wolfers, *Uses and Abuses*, 58 STAN. L. REV. at ___, *supra* note __.

[74] *Id.* at __.

a particular type of crime to use prediction markets to study the likely effects of doing so.[75] 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.

iv. From Correlation to Causation

We have shown how contingent markets can be useful for revealing market-aggregated assessments of conditional expectations, for example, what will the homicide rate be in Chicago conditional on the governor instituting 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 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 the costs of all crime, leading to more crime, including murder, on the margin.[76] 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, analyzing 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

[75] 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.

[76] 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.

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.[77]

We propose the use of markets, called "Prediction IVs",[78] that allow policy makers to simulate exogenous policy shocks as a way of testing the casual significance of the shock.[79] The first step in creating these markets is to think of a plausible and exogenous shock to the policy variable. When evaluating death penalty policy, a U.S. Supreme Court ruling banning capital punishment would be such a shock. 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:[80]

$$\beta = (\text{average } \Delta\text{homicide rate in death penalty states} - \text{average } \Delta\text{homicide rate in non-death penalty states}) / (\text{Average execution rate in death penalty states}_{before}).$$

In the real world, such instrumental variables (or "IVs") are not freely available, and indeed, the Supreme Court hasn't provided an experiment like this since 1972.[81] 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 policy makers would want to

[77] 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.

[78] "IV" here stands for "instrumental variable."

[79] *See* Justin Wolfers and Eric Zitzewitz, *Five Open Questions About Prediction Markets*, in INFORMATION MARKETS: A NEW WAY OF MAKING DECISIONS IN THE PUBLIC AND PRIVATE SECTORS, ED. ROBERT HAHN AND PAUL TETLOCK, AEI-Brookings Joint Center, Washington D.C. (2003).

[80] This Wald Estimator representation is equivalent to a two-stage least squares set-up, running a first-stage equation: $\text{Execution rate}_s^{after} - \text{Execution rate}_s^{before} = \alpha \text{ Active death penalty statute}_s^{before}$, and in the second-stage, estimating $\text{Homicide rate}_s^{after} - \text{Homicide rate}_s^{before} = \beta \text{ Predicted } \Delta\text{Execution rate} + \gamma$.

[81] *See* Furman v. Georgia, 408 U.S. 238 (1972).

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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 policy makers 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, it which case it is too late anyway, a policy maker 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 the death penalty 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 the death penalty 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 isn't, 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 is for 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 policy makers can use to measure causal impact.[82]

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 people for 2005, meaning there were about 14,000 murders in these states.[83] The contracts described above

[82] 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 # 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.

[83] Homicide rates and population are based on 2005 data. *See* [insert cite].

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 percent 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,[84] so the market view of the deterrent effect would be about 18 homicides deterred per execution.[85]

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 potentialmarket 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

A key requirement for any trade to occur is "contractability", meaning one can actually write a contract that clearly presents 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 an indeterminate outcome, since traders' actions in the market might have been based on an interpretation of the contract that was inconsistent with the actual intent of the contract. 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

[84] Ten states executed prisoners in 2007. *See* http://www.deathpenaltyinfo.org/article.php?scid=8&did=186.
Texas accounted for 60 percent 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.

[85] This is simply: (6-2)/32 = 0.13.

it is unclear what a "crime-related death" is, how this 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 be: "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, and a mechanism for resolving 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 doing some thinking on 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.

Since policy makers 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 policy makers 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 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 survey 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 provided by a poll or expert report, can be used to dramatically expand the power of policy making prediction markets. For example, the National Academy of Sciences issues periodic reports on issues such as whether the death penalty is a deterrent. These expert reports, drawn on the

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best thinking of experts in the field, are conducted in a manner designed to yield a deliberative answer that improves over any individual expert view or average, 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 not 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.[86] But we believe these can be overcome. There 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. [87] As a result, if the information that diverse market participants provide through trading is not be able to overcome publicly available information, say, because it is less tangible, less trustworthy, or of less relevance, it is doubtful that the market could improve on any official forecast. For example, InTrade.com floated contracts on whether weapons of mass destruction 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. Since 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

[86] 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 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).

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

the White House. In the crime policy prediction markets we propose, this problem 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 question 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 feel of observant residents, what the doctors in the emergency room are seeing, what the lawyers trying cases know about law enforcement levels, what the prison wardens or guards see among prison populations, etc.

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 there is a "winner-take-all" market that 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 population. The price of this contract can be interpreted as a market-aggregated probability that the event—an FBI report of this murder rate—will occur.[88] 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

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

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by the FBI. The price of this contract will reveal the expected of the 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.[89]An even-money bet reveals the market's expectation of the median outcome, and hence can be interpreted as a forecast that it is as the homicide rate is as likely to be higher than *y*, as lower. 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 also take into account likely market imperfections, including transaction costs and behavioral anomalies. Let's consider an example of each. Although prediction markets can be created in ways that make the actual costs of trading extremely low,[90] 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 a $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 it suggests an opportunity win an expected $5 per $500 committed to the market. 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"

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

[90] Iowa markets work with hundreds of dollars total committed.

binary contracts have proven much more popular with traders in most prediction markets.[91]

Behavioral anomalies that can disable markets generally also have the potential to cause problems with prediction markets.[92] 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".[93] With this evidence of mispricing of very small probabilities in hand, it seems likely that markets may be poorly calibrated over small probability crime events. For most crime forecasting markets we have discussed, this is not likely to be problematic, since 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 be helpful for yielding more useful data. For example, suppose policy makers 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 next state to experience a multiple-victim shooting, may well 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

[91] 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.

[92] *See* SUNSTEIN, INFOTOPIA at 123, *supra* note __; Abramowicz and Henderson, *Prediction Markets for Corporate Governance*, 82 NOTRE DAME L. REV. at 1350, *supra* note __.

[93] *See* Richard H. Thaler and William T. Ziemba, *Anomalies: Parimutuel Betting Markets: Racetracks and Lotteries*, 2 J. ECON. PERSPECT. 161 (1988); Eric C. Snowberg and 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.

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 reflects 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 since presumably a lot of their information would be aggregated by police chiefs.[94] 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 this decision.

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 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 may 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, even thicker 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.[95] Indeed, these uninformed traders provide an even stronger incentive for informed traders to invest in further information discovery and research, and hence likely make the market more efficient.

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

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

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

information one seeks to aggregate is classified, such as FBI intelligence on terrorist threats, then these secrecy needs can only be respected by only 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 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, and if the information asymmetry is strong enough, no trade at all will occur. Barring the insiders from trading does have a cost though, in that arguably the most useful information is not aggregated.[96] Third, there may be 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 policing, neighborhood relations, and so on. These are real issues that will be worked out only through practical experiments and trials.

A reason that is often offered but we think is unpersuasive is the 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 may be a real political roadblock, as policy makers 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, 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 since criminals will

[96] For an interesting proposal for dealing with insider trading within firms, *see* Robin Hanson, "Insider Trading and Prediction Markets," GMU Working Paper (2007) (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), available at http://hanson.gmu.edu/insiderbet.pdf.

not know the underlying statistics of how the market will be resolved, and, in any event, any individual criminal will have a negligible impact on the total number of crimes being forecast. 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 trades that earn large profits can be important signals to 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 prosecutor 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.

D. Liquidity

A key practical concern of many in various prediction markets has been in generating 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",[97] 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.

[97] *See* P. Milgrom and N. Stokey, *Information, trade and common knowledge*, 26 J. Econ. Theory 17 (1982).

In practice, the assumptions underlying this theorem are often violated, and a range of other motivations may lead 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.

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 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 suggest that feelings of community, or reputational concerns can be quite important. The more public and formal the system of prizes is, 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 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 had 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 to a positive-sum game. By analogy, the same incentive for informed traders to participate exists if it isn't 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

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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.[98] He notes that a prominent role for money can trigger repugnance, but that with creative market design, the role for money can be minimized. 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. Interestingly, Robin Hanson notes that much of the political opposition was not in fact to any of the markets that the researchers involved actually proposed.[99]

Even so, 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 would argue

[98] Alvin E. Roth, "Repugnance as a Constraint on Markets", *mimeo*, Harvard University (2007).
[99] *See* Robin Hanson, *Designing Real Terrorism Futures*, 128 PUBLIC CHOICE 257 (2006).

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 market 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.

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 othersstrongly suggests that they may yield better forecasts of future crime levels and certainly would permit more active experimentation on 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 policy makers 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 discussed 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, just as a bid in a prediction market is a bet about some useful piece of information. In 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 information 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 each quarter, to further stimulate interest and attention on 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. 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 track record of useful forecasts.

The lessons learned in terms of participation, contract design, and stakes needed to generation 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 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've just highlighted in this paper, much more experimentation at

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the state and local level will be needed. To that end, the federal government should encourage (and, 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.

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Appendix: Modeling Crime-Market-Policy-Crime Feedback Loop

The main text described a very simple problem: When 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 text. Throughout, we use upper-case letters to denote endogenous variables, and lower-case denotes exogenous factors, while Greek letters refer to parameters (which are assumed common knowledge).[100]

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:

$$Y = x - V \qquad [1]$$

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:

$$V = \beta \textit{ Traditional forecast} + \gamma \textit{ Prediction market price} \qquad [2]$$

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

$$\textit{Traditional forecast} = x+f \qquad [3]$$

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:[101]

$$P = E[Y \mid x+h] \qquad [4]$$

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

[101] 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 ρ_{fh}

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 market price is a forecast 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:

$$\begin{aligned} P &= E[Y \mid x+h] = (x+h)\, E[(x+h)Y] / E[(x+h)^2] \\ &= (x+h)\, E[(x+h)(X - \beta(x+f) - \gamma P)] / E[(x+h)^2] \\ &= (x+h)\, \{(1-\beta)\, \sigma_x^2 - \beta\sigma_{fh} - \gamma\, E[(x+h)P] \} / (\sigma_x^2 + \sigma_h^2) \end{aligned} \qquad [5]$$

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:

$$\begin{aligned} E[(x+h)\, P] &= E[\, (x+h)\, (x+h)\, \{(1-\beta)\, \sigma_x^2 - \beta\sigma_{fh} - \gamma\, E[(x+h)\, P] \} / (\sigma_x^2 + \sigma_h^2)] \\ &= [\, (1-\beta)\, \sigma_x^2 - \beta\sigma_{fh}\,] / (1 + \gamma) \end{aligned} \qquad [6]$$

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

$$P = E[Y|x+h] = (x+h)\, \{[\, (1-\beta)\, \sigma_x^2 - \beta\rho_{fh}\sigma_f\sigma_h\,] / (\sigma_x^2 + \sigma_h^2)\, (1+\gamma)\} \qquad [7]$$

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 allowing 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 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, policy makers 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, 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 policy maker 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.[102] This means that prediction market prices are still valuable for policy makers in all conceivable cases, even when reactions to underlying crime factors are wildly over-aggressive.

[102] 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.

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 has 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:

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

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 lower the crime rate, relative to if a forecast error had not occurred.

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