

Estimating Risk: Stereotype Amplification and the Perceived Risk of Criminal Victimization

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This paper considers the process by which individuals estimate the risk of adverse events, with particular attention to the social context in which risk estimates are formed. We compare subjective probability estimates of crime victimization to actual victimization experiences among respondents from the 1994 to 2002 waves of the Survey of Economic Expectations (Dominitz and Manski 2002). Using zip code identifiers, we then match these survey data to local area characteristics from the census. The results show that: (1) the risk of criminal victimization is significantly overestimated relative to actual rates of victimization or other negative events; (2) neighborhood racial composition is strongly associated with perceived risk of victimization, whereas actual victimization risk is driven by nonracial neighborhood characteristics; and (3) white respondents appear more strongly affected by racial composition than nonwhites in forming their estimates of risk. We argue these results support a model of stereotype amplification in the formation of risk estimates. Implications for persistent racial inequality are considered.

Keywords: risk estimation, stereotypes, neighborhoods, race, victimization

As individuals, we face risk and uncertainty often in our everyday lives. In many cases, we learn to adequately assess levels of risk and modify our behavior accordingly: The sky is gray and overcast, and so we bring an umbrella. In other cases, forming accurate risk assessments is more complicated: Stock market investments, for example, present substantial risks often

with no clear cut strategy for avoiding loss. The sociology of risk literature has primarily focused on the risk of rare events, such as large-scale technological failures or natural disasters, often emphasizing the process by which “experts” generate perceptions of risk and the organizational contexts in which these risk estimates are formed (e.g., Vaughan 1990; Beck 1992; see Heimer 1988 for a review). Everyday forms of risk, by contrast, have received comparatively little attention in the sociology of risk literature. This is true despite the fact that the consequences of everyday risk assessments have been widely recognized in sociological research: Home seekers’ assessments of the risk of crime in a given neighborhood affect their residential decisions (Harris 1999); employers’ estimates of the risk associated with particular applicant characteristics affect their hiring decisions (Holzer 1996); and estimates of the risk of detection and

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Earlier versions of this paper were presented at the Institute for Policy Research at Northwestern University in November 2005; the University of Illinois at Chicago in November 2005; the University of Illinois at Urbana-Champaign in December 2005; the Office of Population Research at Princeton University in December 2005; and the meetings of the American Sociological Association in Montreal, Canada in August 2006. We thank these audiences for helpful comments.

punishment affect youth decisions about delinquency and criminal involvement (Matsueda, Kreager, and Huizinga 2006).

How are estimates of risk calculated? According to certain perspectives, risk estimation represents a straightforward process. Many rational-choice economic models, for example, portray individuals as rational consumers and processors of information, able to make informed predictions about the likelihood of future events. Other perspectives, by contrast, challenge the notion that estimates of risk are the simple product of objective information. Social and cognitive psychological experiments, for example, demonstrate countless examples in which judgment and decision-making are distorted or flawed due to the difficulties inherent in estimating complex probabilities or as the result of extraneous or distracting information (Tversky and Kahneman 1974). Research in sociology and anthropology has likewise identified several instances where the social and cultural contexts shape perceptions of risk (Douglas and Wildavsky 1982; Short 1984). Are individuals poor at assessing the important risks facing them in everyday life? Under what conditions are risk estimates likely to be compromised?

This study takes as its specific focus estimates of the risk of criminal victimization. We observe that, quite unlike estimates of the risk of job loss or the loss of health care, which are remarkably accurate, estimates of the risk of criminal victimization are substantially exaggerated relative to observed victimization rates. In this paper, we seek to explain these inaccuracies by looking to the social contexts in which risk estimates are made. In particular, we look to the influence of neighborhood racial composition and other neighborhood characteristics as key predictors of both expected and observed criminal victimization. The case of criminal victimization provides a useful illustration of the social context of risk formation, allowing us to observe the ways that stereotype-consistent social cues can distort risk assessment, a process we refer to as stereotype amplification.

THE BASIS OF RISK PERCEPTIONS

In traditional rational-choice models of how decisions are formed, risks are taken as known to individuals. The action any individual is expected to take depends on maximizing expected utility, with uncertainty represented through the probabilities of possible outcomes conditional on the action chosen. The total utility of any given course of action is found by multiplying the utility (or disutility) of various outcomes by their probabilities. The accuracy of the risk estimates is usually taken to be true by assumption (Manski 2004).

Although assumptions of accuracy in risk estimation continue to be used in many rational choice and economic models, other evidence suggests that these assumptions are often unfounded. In psychology, for instance, a long line of experimental studies has documented the range of heuristics individuals use to estimate risk and make decisions under uncertainty, with many heuristics systematically deviating from rules established in statistical and probability theory. Among many heuristics that lead to suboptimal decisions, individuals often ignore information about base-rates, show overconfidence in information from small samples, and judge frequency based on their ability to recall similar incidents (see Kahneman, Slovic, and Tversky 1982). These studies have shown not only that individuals often make errors in judging risk and uncertainty, but that many errors tend to be systematic and predictable (Payne, Bettman, and Johnson 1992; Arieli 2008; but see Christensen-Szalanski and Beach 1984).

Psychological studies have also found a number of ways in which logically irrelevant changes in the framing of a decision can influence judgments. In laboratory and survey settings, information which is given emphasis through the choice of reporting categories—for example, reporting chance of death as against chance of survival—often influence decisions and judgments (Slovic, Fischhoff, and Lichtenstein 2000a). Likewise, irrelevant initial starting points provided by investigators have been shown to influence probability estimates of risk (Tversky and Kahneman 1974). These

studies point toward the relevance of social influences by varying the situational context of risk assessment. Laboratory studies, however, continue to focus primarily on cognitive rules and micro-contexts in which individual decisions are made. This literature provides few insights into how factors beyond the immediate situation influence decisions (see also Short 1984; Zerubavel 1997).

Studies in sociology, non-experimental psychology, communication, and anthropology, by contrast, have examined a number of broader factors that influence risk perceptions (Slovic 1987). Many of these factors are summarized in the “social amplification of risk” framework, developed by Kaspelson and colleagues (1988). The social amplification of risk summarizes the multiple levels at which risk-relevant public events—such as a nuclear reactor accident—are amplified or attenuated in the public understanding. Amplification (or attenuation) of risk messages can occur both at the point at which messages are sent (e.g., the media) and points at which messages are received (e.g., individuals). The media, for instance, can intensify a signal by providing more extensive coverage to an event or story. Individuals can also amplify or attenuate signals by attaching social values and meanings to the information which give it greater or lesser significance. The social amplification perspective thus provides a framework for understanding the range of factors that may increase or decrease perceptions of the importance of events related to a risk. Rather than accepting a simple model of risk and response, this perspective encourages us to consider the social and cultural context in which risks become highlighted or downplayed (see also Douglas and Wildavsky 1982; Savelsberg 1994; Vaughan and Seifert 1992).

Building from this previous literature, we aim to provide an empirical analysis of the social context in which estimates of risk are formed. In particular, we are interested in the cues individuals draw upon to interpret risks of criminal victimization. Victimization presents an interesting case from the perspective of risk formation: Unlike cases of large-scale disaster or technological failure which

are the focus of most of the sociological research on risk, crime occurs on a more regular basis; people thus have reason to think about the risks of crime in their daily lives. Likewise, information about the frequency and severity of crime in a local area is available to nonspecialists, through personal experience and observation, crime reports, and other sources of information. Individuals thus have access to a wide range of information and direct experiences against which to calibrate their perceptions of crime. In their everyday assessments, then, how accurately do individuals perceive the risk that they will become the victim of crime? What social cues do individuals use in forming these risk estimates, and to what consequence? It is to these questions that we turn in the remainder of our discussion.

The Social Context of Crime Perceptions

In constructing estimates of the risk of an adverse event, information about the frequency and likelihood of that event represent important considerations. Not surprisingly, studies investigating perceptions of crime note that local area crime rates represent an important influence, confirming assumptions that individuals do perceive and rely upon relevant objective factors in forming their estimates of risk (McPherson 1978). Because actual crime rates are not typically known or fully observed, however, individuals are likely to look to other social or contextual factors associated with crime for additional information in forming risk estimates.¹ For example, research has shown that individuals rely on information about the surrounding area, such as signs of disorder, incivilities, and demographic characteristics of a local area in forming their perceived risk of victimization or fear of crime (Ferraro and LaGrange 1987; Perkins and Taylor 1996).

¹ The process by which acts are labeled “crimes” is itself socially constructed and can be subject to gender and race biases (see Hagan and Foster 2006). We use the term “actual crime” to correspond to specifically defined acts as described in the methods section.

Though a wide range of influences contribute to respondents' perceptions of risk, one variable that has received among the most extensive consideration concerns the influence of race. Research consistently finds that Americans hold strong associations between race and crime, and appear especially fearful about the risk of crime in the presence of black strangers. In experiments in which black and white figures perform identical acts, for example, the black figure's behavior is usually seen as more threatening and predatory than the white figure's behavior (Duncan 1976; Sagar and Schofield 1980). Likewise, in surveys asking about fear of strangers in hypothetical situations, respondents are more fearful of being victimized by black strangers than by white strangers (St. John and Heald-Moore 1995, 1996). These studies suggest that, when assessing the risk posed by potential perpetrators, race represents a highly salient cue.

The effects of race on perceptions of crime have been shown to operate at more aggregate levels as well. Because crime is a highly spatially patterned phenomenon, and because neighborhoods tend to be highly segregated on the basis of race, there often exist strong mental associations between neighborhood racial composition and neighborhood crime. Indeed, several studies have found that the percentage black in a population is positively associated with fear of crime and perceived severity of the neighborhood crime problem (e.g., Covington and Taylor 1991; Chiricos, Hogan, and Gertz 1997; Quillian and Pager 2001). Such findings suggest that individuals will perceive greater risks of victimization in environments that have a higher percentage of black residents.

That individuals use information about racial composition and other social characteristics in shaping their assessments of crime is well known. Few studies, however, have made efforts to determine the relative accuracy of these perceptions by contrasting the perceived association to actual associations. As a result, it is often unclear whether the strong associations between race and crime represent accurate group-level estimates—suggesting the cognitive utility of race cues

for estimating danger—or whether these associations distort the true relationship between the racial composition of a local area and the risk of crime. Using a unique source of data with information about both estimated and realized events, our study directly addresses this question in an effort to provide greater understanding of how individuals process social cues in forming estimates of personal risk.

A Model of Crime-risk Estimation

In investigating the link between social cues and risk estimation, we consider a range of possible pathways through which direct and indirect information about crime is converted into estimates of risk. Figure 1 presents a conceptual model of crime-risk estimation, in which estimates of crime are a function of multiple sources of information. Actual victimization rates represent a key component of the model; the victimization rate is in turn correlated with a range of social conditions, such as the neighborhood racial composition, local economic conditions, and other contextual characteristics (e.g., quality of the housing stock, signs of social disorder, etc.). There is no causal pathway implied by this association, which simply reflects the well-established bivariate associations between crime and various social contexts (e.g., Sampson 1987; Bursik and Grasmick 1993). Because crime rates cannot be completely observed, our model predicts that individuals also rely on the social conditions of a local area in forming their estimates of personal risk. Estimates of risk then are a function of both actual crime rates and information about the social conditions in which crime is likely to flourish.

Figure 1 presents two additional pathways through which information about crime rates and social conditions may be converted into estimates of risk. In the first case, described as “statistical discrimination,” individuals are able to correctly assess the relationship between social conditions and crime, using information about group-level characteristics to make accurate assessments of risk. In the case of race, for example, demographic studies

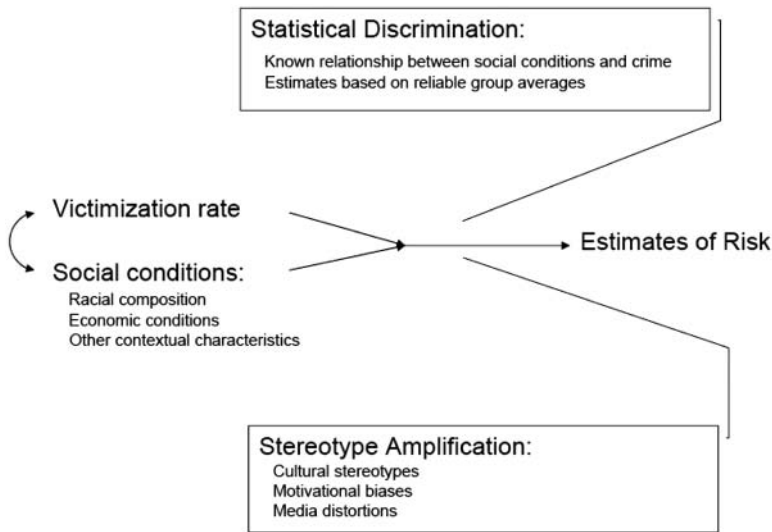


Figure 1. A Conceptual Model of Crime-risk Estimation

clearly show that there is a bivariate association between neighborhood racial composition and levels of street crime. This does not mean the use of this information is desirable or morally justified, but from a practical standpoint, in many instances the use of information about local racial composition could improve the average predictive accuracy of judgments. Likewise, models of statistical discrimination from the economics literature often assume that generalizations about group characteristics are based on statistically accurate empirical realities that can improve decision-making in the face of uncertainty (Phelps 1972; Arrow 1972). Schwab (1986) makes explicit the connection of statistical discrimination and stereotyping. As he notes, statistical discrimination is discrimination grounded in a “true stereotype,” in which the decision maker “responds only to correct group information (statements that are indeed true on average)” (228; for a similar psychological perspective, see Lee, Jussim, and McCauley 1995; Arkes and Tetlock 2004). According to this model, then, social cues such as neighborhood racial composition are correctly perceived by individuals as predictive of the level of risk in a given area.

A different set of predictions is represented by the second mediating pathway in Figure 1, labeled “stereotype amplification.” According to this perspective, real associations between crime rates and particular social conditions become exaggerated or distorted through various channels, including the influence of cultural stereotypes, skewed media coverage, perceptions of group threat, and other nonsystematic sources of information. Following LaPiere (1936)—one of the first sociologists to identify systematic distortions in the content of ethnic stereotypes—this perspective questions whether the information conveyed by racial composition is accurately perceived and interpreted (see also Quillian 2006). In the case of the race–crime relationship, for example, rather than perceiving the correct degree of association, respondents may rely on stereotypes that provide exaggerated or inaccurate representations. As noted above, racial stereotypes of blacks as violent or crime-prone are among the most salient dimensions of contemporary stereotypes about African Americans (Smith 1991; Devine 1989), and are associated with exaggerated perceptions of the race–crime relationship. A 1991 survey, for example, asked, “Of all the people arrested for violent crimes

in the United States last year, what percent do you think were black?" The modal response to this question was "60 percent," an exaggeration by roughly 35 percent of the actual proportion at that time.² These negative stereotypes are likely shaped by widespread media coverage, which tends to exaggerate the frequency of crime and to present images of crime in a heavily racialized context (Entman 1990; Dixon and Linz 2000; Gilliam et al. 1996).³ Likewise, a long tradition of sociological studies of racial threat suggests that as a subordinate racial group grows in size, its members come to be viewed as increasingly threatening to the interests of the dominant group and negative attitudes about that group intensify (Blalock 1967; Taylor 1998; Scheepers, Gijsberts, and Coenders 2002); however, past studies find that the relationship between group size and hostile attitudes applies only at large spatial scales.⁴ To the extent that

cultural stereotypes, media imagery, threat-motivated evaluations, or other factors produce distortions in perceptions of risk and of the relationship between particular social groups and the likelihood of risky events, relying on social cues will in some cases compromise the accuracy of risk estimates.

The model above presents two competing representations of the process by which contextual information may be translated into perceptions of personal risk. Of course, the relevance of each pathway may further depend on characteristics of the individual perceiver. In particular, it is worth considering whether our model of crime-risk estimation may differ depending on the race of the respondent. While some research indicates that dominant cultural stereotypes affect even members of stereotyped groups (Sagar and Schofield 1980; Correll, Wittenbrink, and Judd 2002), other research suggests that racial minorities are better able to look beyond the influence of stereotypes in assessing the characteristics of particular minority individuals or neighborhoods (Judd and Park 1993; Quillian and Pager 2001). If blacks and/or Hispanics are better able to recognize individuating information about members of their own group, they may be better able to translate information about contextual characteristics, such as racial composition, into more accurate risk estimates (Anderson 1990). The process by which crime rates and contextual characteristics are translated into estimates of risk, then, may further depend on the race of the perceiver.

Past Studies of Neighborhood Racial Composition and Perceptions of Crime

The critical emphasis of our model of crime-risk estimation concerns the process by which social context characteristics—crime rates, racial composition, and other local area conditions—are translated into perceptions of risk. A number of past studies have examined the relationship between race of neighborhood and perception of crime levels, finding that the percent black of a neighborhood population is positively associated with fear of crime (Moeller 1989; St. John and Heald-Moore 1995; see

² This survey item comes from the 1991 National Race and Politics Survey, <http://sda.berkeley.edu:7502/archive.htm>.

³ The study of media effects on fear of crime is itself a large and complex literature. Media effects are not monolithic, but rather vary according to the type of media, characteristics of the viewer, and other situational effects including neighborhood racial composition (Eschholz, Chiricos, and Gertz 2003; Heath and Gilbert 1996). Experimental research shows strong effects of local television news on perceptions and fear of crime, and on racialized attitudes about crime. An experiment by Gilliam and Iyengar (2000), for example, shows that exposure to news coverage of a violent incident committed by a black perpetrator both increases punitive attitudes about crime and further increases negative attitudes about blacks generally. Political initiatives emphasizing "tough on crime" approaches likewise have been implicated in raising public anxiety over crime (Glassner 1999; Mendelberg 2001; Beckett, 1997).

⁴ Empirical studies consistent with the threat hypothesis have typically used the share minority calculated over large geographic areas such as countries, U.S. states, or metropolitan areas. By contrast, studies using smaller spatial units such as the neighborhood or school have more often found the opposite relationship to hold: Several studies have found that larger shares of subordinate groups in neighborhoods, schools, and small districts are associated with positive perceptions of subordinate group members by members of the dominant group in these contexts (Wagner et al. 2006; Forman 2007; Tolma, Lubbers, and Coenders 2008).

also reviews in Skogan 1995 and Chiricos, McEntire, and Gertz 2001). While this evidence suggests that respondents use information on social conditions—and, in particular, racial composition—in making assessments of victimization risk, it remains unclear whether and under what conditions the use of this information improves individual risk estimates. Most studies in this tradition have not included measures of actual rates of crime or victimization in the neighborhood against which to calibrate respondents' perceptions.⁵ This research then avoids the key question of whether the perceived association between neighborhood racial composition and crime reflects an unfortunate (but accurate) social reality, thus improving risk estimates, or whether this association becomes reliably inflated or distorted through the process of amplification described above, thus influencing risk estimates in ways that compromise accuracy.

A few studies have made efforts to disentangle the degree to which the race–crime association reflects an accurate depiction of the underlying reality. An early study by McPherson (1978) found that perceptions of crime closely mirrored realities of crime, whereas recent studies by Chiricos, Hogan, and Gertz (1997), Chiricos, McEntire, and Gertz (2001), and Quillian and Pager (2001) find evidence of bias in assessments of the relationship between neighborhood racial composition and perceived neighborhood safety or the severity of crime as a neighborhood problem (see also Sampson and Raudenbush 2004 on perceptions of disorder). Yet there are important limitations to the conclusions we can draw from these studies regarding accuracy in perceptions of crime risk. One significant limitation of the Chiricos et al. (1997, 2001) studies is their reliance on measures of *perceived* racial composition rather than actual racial composition. Though the disconnect between these two

measures is interesting in its own right, reliance on perceptions of racial composition as a predictor of perceived neighborhood crime leaves the direction of causality quite uncertain. It may be the case, for example, that high-crime neighborhoods lead to perceptions of greater minority concentrations rather than the other way around—limiting our ability to draw conclusions about causal effects from the results. A more fundamental limitation of this literature (including Chiricos et al. 1997, 2001) results from the reliance on official crime statistics to assess the level of actual neighborhood crime. Because a significant share of crime is never reported to police, especially for property crimes, official statistics have significant measurement error as indicators of actual crime (Bureau of Justice Statistics 2003). Of particular concern, suspicion of the police in minority neighborhoods may lead to greater underreporting, creating a source of systematic bias in measurement linked to neighborhood racial composition. Under this scenario, estimates of the relationship between neighborhood racial composition and crime rates would be artificially suppressed. Quillian and Pager (2001) improve on the situation by using measures of both crimes reported to the police and local-area victimization surveys against which to calibrate respondents' perceptions of crime. Despite this advance, the victimization surveys used were based on small samples in each neighborhood, thus providing only an incomplete proxy for area victimization rates. Ultimately, then, while a few previous studies have taken the important step of including measures of actual crime rates in their analyses, official police reports or small-area estimates from victimization surveys represent incomplete proxies for neighborhood crime rates and may leave the results vulnerable to systematic forms of bias.

The available comparisons thus all point to a crucial issue in drawing conclusions about accuracy or bias in risk assessment: comparability between risk assessments and measures of actual risks. The present study makes headway along these lines by using a unique survey design that allows for direct comparison of estimated risks and rates of realized risks.

⁵ Many studies include controls for respondents' prior experiences of victimization. Though clearly related to perceptions or fear of crime, this variable does not capture the aggregate risk profiles of respondents against which one could calibrate their predictions of neighborhood crime.

Measuring Perceptions of Victimization Risk

A large literature in sociology and criminology investigates factors associated with fear of crime (see Bursik and Grasmick 1993, chapter 3, for a review). While establishing that individuals learn about crime events from many sources—most notably the media and personal acquaintances (Skogan and Maxfield 1981; Bursik and Gramisk 1993, chapter 3)—this literature does not assess whether and to what extent these sources of information enhance or distort the accuracy of individual perceptions. Further, past studies generally focus on fear of crime rather than risk. Where perceived risk refers specifically to the expected chance of victimization, fear conflates both perceived risk of becoming a victim and the perceived consequences of victimization (Warr and Stafford 1983; Rountree and Land 1996). Because perceived risk avoids the subjective evaluation of consequences, this measure can be meaningfully compared with rates of crime victimization.

A small number of studies have compared perceived risks of crime to realized rates available in population statistics. Slovic et al. (2000b), for instance, asked respondents to estimate the rates of several causes of death. They found evidence of overestimation of risks of homicide relative to diseases with high fatality risks like diabetes or suicide, for instance. While this approach does allow a comparison of subjective expectations and actual event rates, the estimates thus produced are not the same as estimates of personal risk—perceived risk to one's self—which is most relevant to the actions individuals take in response to risk. An individual can assess a risk as occurring frequently in the population even if they view their personal risk from that event as minimal. Comparing subjective and objective risks is more difficult because of the challenges inherent in identifying individuals in comparable situations, defined by the most relevant indicators of risk.

Moving from a focus on measures of fear to estimates of risk, and from population rates

to personal risk, this study uses a unique source of data that makes possible the direct comparison of estimated and realized risks. In the following analyses, we investigate: (1) the accuracy of risk estimates across a range of negative events; (2) the relationship between social context variables, especially racial composition, and estimates of risk; and (3) the extent to which the effects of racial composition differ according to the race of the perceiver. The direct comparison of individuals' estimated risks with realized events provides a rare opportunity to examine the accuracy of personal risk perceptions, and to help us better understand the process by which social context characteristics shape the perceived likelihood and actual occurrence of risky events.

DATA

We use data from the Survey of Economic Expectations, a national repeated cross-sectional survey conducted by the University of Wisconsin Survey Center from 1994 to 2002. The survey was a telephone poll based on random digit dialing, with a 50 percent response rate. The survey included basic demographic questions, questions asking about perceptions and experience with crime, and expectations of future economic events (for more details on the survey design and response rates, see Dominitz and Manski 2002). Fortunately, the survey also contains respondent zip code information, allowing us to match the survey data with a range of contextual characteristics obtained from two waves of the decennial census.

Measuring Anticipated and Actual Probabilities of Negative Events

The perceived and actual crime measures are based on questions that ask respondents to evaluate the risk of future events. In a series of cross-sectional surveys about a year apart, respondents were asked to evaluate the chance (on a 0 to 100 scale) that a variety of negative events would occur during the

next year. Respondents were also asked if these same events have occurred to them during the last year. By comparing each survey's estimate of expected risk with the following year's realized incidents, a fairly exact comparison of (aggregate) subjective estimates of personal risk and their objective occurrence is possible. The questions asking about the risk of future events begin with the following statement:

Now I will ask you some questions about future, uncertain outcomes. In each case, try to think about the whole range of possible outcomes and think about how likely they are to occur during the next 12 months. In some of the questions, I will ask you about the PERCENT CHANCE of something happening. The percent chance must be a number from zero to one hundred. Numbers like 2 or 5 percent may be "almost no chance," 20 percent or so may mean "not much chance," a 45 or 55 percent chance may be a "pretty even chance," and a 95 or 98 percent chance may be "almost certain." The percent chance can also be thought of as a number of chances out of 100.

Respondents were asked about two crime events, burglary and robbery:

Burglary: "What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that someone will break into (or somehow illegally enter) your home and steal something, during the next 12 months?"

Robbery: "What do you think is the PERCENT CHANCE (what are the CHANCES OUT OF 100) that someone will take something directly from you by using force—such as a stickup, mugging, or threat—during the next 12 months?"

Respondents were also asked to give percent chances of losing their job within the next year and their chance of having health insurance one year from now.

No Health Insurance: "Now please think about your health insurance coverage 12

months from now. What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that you will have health insurance coverage 12 months from now?" [We subtract the answer from 100 to give the measures a consistent coding of high values indicating negative events (no health insurance).]

Job Loss: "I would like you to think about your employment prospects over the next 12 months. What do you think is the PERCENT CHANCE that you will lose your job during the next 12 months?"

Parallel questions are asked about actual occurrences of these events in the last year:

Burglary: "During the past 12 months, did anyone break into or somehow illegally get into your home and steal something?"

Robbery: "During the past 12 months, did anyone take something directly from you by using force—such as a stickup, mugging, or threat?"

No Health Insurance: "Do you have any health insurance coverage?" "No" is coded 1 and "yes" 0.

Job Loss: "Have there been any times during the past 12 months when you did not have a job and were looking for work?"⁶

The annual waves of the Survey of Economic Expectations (SEE) represent repeated cross-sections, not a panel, and thus comparisons of risk estimates and victimization for specific individuals are not possible. We can, however, compare average predicted rates of crime events with the rate at which the same event occurs among respondents in the following wave of the survey. For example,

⁶ This realization question corresponds less well to the estimated risk question than is the case for the other risk events we consider. See Dominitz and Manski (1997), footnote 12, for a discussion of the difference in phrasing across these items.

respondents' estimates of their risk of victimization in 1998 (looking forward) can be meaningfully compared to the actual victimization experiences of respondents reporting in 1999 (looking backward), offering a comparable window of exposure. Correspondingly, we can examine how individual and contextual factors predict the estimations and realizations, allowing us to examine the accuracy of the use of predictive factors by contrasting their associations with estimates of risk and their associations with realizations of risk.

The ability to make a particularly well-matched comparison of estimated risks and actual rates of risk events is a unique strength of the SEE data. The survey and realized risk questions are constructed to be parallel in wording and to ask about crime events over a similar time frame. And because they are asked as part of the same ongoing survey project, we can be sure that the estimation and realization samples represent the same populations for comparisons of risk estimates. By contrast, comparisons of expectations and realizations from separate sources cannot be as well matched, due to differences in question wording, time frame, sampling frame, nonresponse, undercoverage, and other factors which invariably introduce error into comparisons between measures of expected and actual crime rates.

Rather than comparing estimates of risk and victimization experiences one year at a time, we pool together responses to the expectations and realizations data across years in the analysis to make comparisons of estimated and realized risk. To increase comparability in the time frame of expectations and realizations, the first wave of the survey for realizations and the last wave for expectations were dropped from the data. We thus compare pooled expectations data—looking forward 12 months—from surveys from 1994 to 2003 with actual experiences of victimization—reporting over the prior 12 months—from pooled surveys from 1995 to 2004.

Can Respondents Meaningfully Answer Probabilistic Questions about Risk?

Before turning to our analysis, it is worth considering whether respondents can meaningfully respond to questions of risk assessment in quantitative terms. Do the answers to survey questions accurately reflect the degree of perceived risk by respondents, or does the exercise of estimating quantitative probabilities skew or distort respondents' answers? This question is dealt with at length in Dominitz and Manski (1997) and Manski (2004). In the data, several facts about the patterns of responses suggest that the data approximate actual subjective estimates of risk that guide decisions. First, rates of non-response to these questions are very low (below 3 percent), suggesting that respondents feel comfortable providing answers to these questions. Second, demographic groups (defined by age, race, sex, income, education, etc.) with higher actual risks of an event tend to have higher estimated risks, suggesting that the quantitative estimates accurately map the observed distribution of risk. Finally, as we show below, respondents are capable of providing quite accurate risk estimates in certain domains.

In Figure 2, we present a basic comparison of estimated and realized risk for each of the four events: job loss, being without health insurance, burglary, and robbery, as discussed above. As the comparisons for the first two risk types make clear, respondents are capable of making extremely accurate predictions about the risk of certain future events. Mean estimates of the risk of job loss (14.5 percent) are close to the actual rate of job loss among survey respondents one year later (12.9 percent). Likewise, estimates of the risk of not having health insurance in a year's time (14 percent) come within a few percentage points of the actual rate (11.7 percent).

In stark contrast, both estimates of the risk of criminal victimization (burglary and robbery) indicate a substantial exaggeration

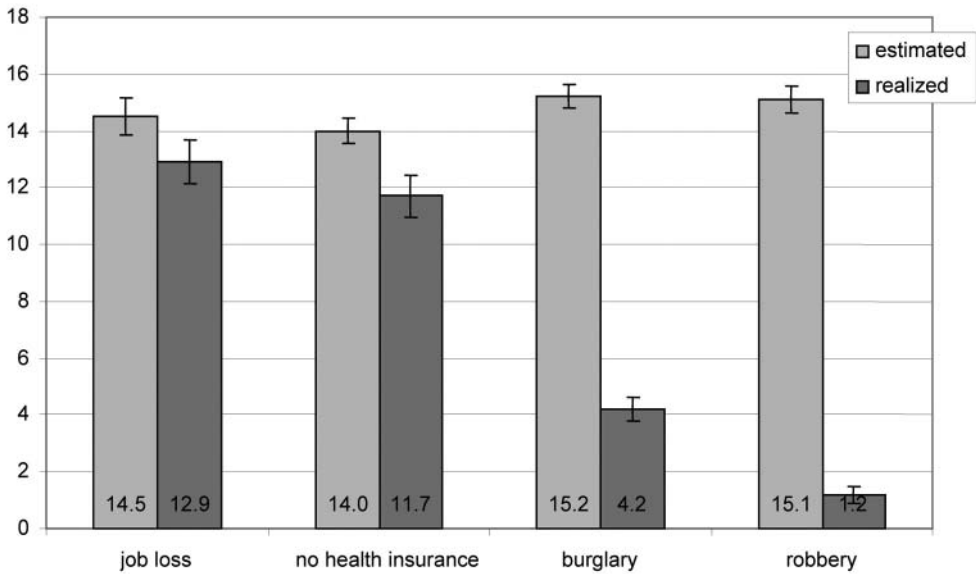


Figure 2. Estimated and Realized Risks, by Type of Risk. Estimated risks represent the mean probability estimate of the event occurring in the next 12 months. Realized rates represent the proportion of sample respondents experiencing the event in the previous 12 months. Responses for estimated and realized victimization are averaged across survey waves; the first wave of data on realizations and the last wave of data on expectations were dropped to create comparable time-frames for the analyses. Error bars represent 95 percent confidence intervals for both estimated and realized risks.

of risk relative to realized victimization rates. Estimates of the risk of burglary are more than four times greater than realized risks (15.2 vs. 4.2 percent); estimates of the risk of robbery are nearly 13 times higher than actual risks (15.1 vs. 1.2 percent). Taking

into account the possible concern that overestimation in these cases is driven by a few respondents giving very high risk estimates, we look also to the median estimated risk, which is not affected by the skewing effect of outlier responses. Median estimates show a pattern of overestimation nearly as extreme as the mean: The median estimated risk is 10 percent for burglary and 10 percent for robbery, far above the realized rates. These findings replicate and extend earlier results reported regarding burglary risk by Dominitz and Manski (1997). Where respondents have little difficulty estimating the risks of adverse economic events, their estimates of the risk of victimization are exaggerated by a substantial margin.⁷

Are Smaller Risks Too Difficult to Estimate?

The above comparisons demonstrate that individuals can be quite accurate in estimating risks of certain adverse events. In fact, in the

⁷ One possible factor contributing to exaggerated estimates of burglary and robbery risk is that crime rates dropped nationally during the period of the study. Although the time frame for estimates and realization are matched, we might expect some overestimation if respondents did not adequately account for the ongoing secular drop in crime. In the SEE data, we found that estimates of burglary and robbery victimization actually fell more quickly than realizations from the beginning to the end of the study period, suggesting that information and awareness of the crime drop produced sharper reductions in estimates than warranted given realization rates for crimes the SEE considers. In addition, the gap between estimates and realizations of crime is orders of magnitude larger than any year to year variation in crime rates might produce. Comparing estimations with realizations for any year in our survey, the prevalence of both burglary and robbery are highly overestimated relative to actual rates.

Table 1. Accuracy of Estimates for Groups with Overlapping Realized Risk Levels

Risk Event	Subgroup	Mean Risks		Difference
		Estimated	Realized	
Job loss	White, college graduates	11.97 (0.45)	10.41 (0.56)	1.56
	Nonwhite HS degree or less	26.55 (2.08)	25.26 (2.20)	1.29
No health insurance	White, college graduates	9.27 (0.36)	7.01 (0.48)	2.27
	Nonwhite HS degree or less	29.40 (1.66)	27.72 (2.31)	1.68
Burglary	White, college graduates	13.00 (0.29)	3.23 (0.32)	9.76
	Nonwhite HS degree or less	22.16 (1.36)	8.29 (1.45)	13.87
Robbery	White, college graduates	12.66 (0.32)	0.85 (0.19)	11.81
	Nonwhite HS Degree or Less	23.20 (1.56)	3.75 (1.17)	19.46

Note: Key contrast groups shown in bold. Standard errors in parentheses. Standard errors adjusted for clustering on zip code. The difference column is not always equal to the expected minus realized columns due to rounding.

cases of job loss and insurance loss, respondents demonstrate remarkable accuracy in estimating relevant probabilities. Why then are risks of burglary and robbery so overestimated relative to other adverse events? Before turning to an investigation of possible substantive explanations, it is worth considering a specific property of crime risks that differentiate them from other adverse events. In particular, it may be the case that respondents are especially poor at estimating the likelihood of extremely rare events. Because the actual risk of criminal victimization is sizably lower than the actual risks of job loss or being without health insurance, the differential baseline may itself produce some distortion. Note that estimated risks for all four outcomes hover around 14 or 15 percent. Only the crime variables, by contrast, demonstrate much lower realized rates. It may be the case, then, that respondents find it difficult to estimate risks much below 15 percent, and thus are more likely to exaggerate the risk of rare events.

We investigate this possibility by analyzing subsets of the sample for whom realized rates of job loss or insurance loss correspond to realized rates of criminal victimization. By looking at the range of outcomes among subgroups with overlapping risk levels, we can directly examine differing base rates as a possible source of inaccuracies in estimates. Table 1 illustrates these comparisons by presenting the estimated and realized risks of

two subgroups that demonstrate overlapping realized risks across the four risk types. One subgroup includes whites with college degrees, the other nonwhites with high school degrees or less; these two groups represent populations with sufficiently different risk profiles to allow for overlapping risk levels across the four risk outcomes (job loss, insurance loss, burglary, and robbery). Specifically, whites with college degrees have lower than average risks of job loss and insurance loss (between 7 and 10 percent), while nonwhites with less education have elevated risks of burglary or robbery (between 4 and 8 percent). Given these overlapping risk profiles, we can investigate the extent to which the accuracy of risk estimates depends on the baseline level of risk.

Looking to the first set of categories presented in bold in Table 1, we see that estimates of job loss and insurance loss remain quite accurate, even among the low-risk group of white college graduates. As with the full sample, estimates of risk tend to differ from actual risks by only about 2 percentage points. The same pattern does not arise for estimates of criminal victimization, even among those subsamples with higher victimization rates. For example, nonwhites with lower levels of schooling have burglary victimization rates of about 8 percent, far higher than the sample as a whole. Nevertheless, estimates of burglary risk among this group are correspondingly elevated, at 22 percent,

mirroring the exaggerated risk estimates of the larger sample. In general, burglary and robbery rates are overestimated among groups at all levels of realized risk, while job loss and insurance loss estimates are fairly close to realized rates at all levels of realized risks. It does not appear to be the case, then, that low base rates are the driving force behind exaggerated estimates of criminal victimization.⁸

Moving from possible methodological explanations to substantive ones, we turn next to an examination of the social context in which risk estimates are formed. Drawing on the contextual theories of risk estimation discussed above, this approach encourages us to consider the range of environmental cues respondents may look to in forming estimates of their risk of victimization. In the following analysis, we consider the social and demographic characteristics of the respondent and his/her surroundings in attempting to explain variation in estimates of risk. In particular, because of strong associations between race and crime, we examine the influence of the local area racial composition on respondents' estimates of risk.

A Contextual Analysis of Risk Formation

Our models of perceived risk incorporate predictors to capture both individual and local area characteristics. First, we include individual characteristics that may be related to perceived and actual risk, including measures of income, race, gender, and age. Previous literature finds, for instance, that women are more fearful of crime than men, and the elderly more fearful of crime than the non-elderly; these findings may or may not hold as well for perceived risk (Rountree and Land 1996). These variables are taken from respondent self-reports on the Survey of Economic Expectations (SEE). We also include dummy variables for each of the survey years to control for any year-specific factors. We do not include past victimization experience as

a predictor of future risk estimate in the final models, because we want the models to be parallel with models of actual risk events.⁹ Second, we incorporate measures of the characteristics of the local area the respondent resides in, including the concentration of African Americans and Hispanics, local area economic conditions (including the concentration of family poverty and per capita income), the concentration of immigrants, the concentration of young men, the proportion of vacant housing units, the population density, and the urban status of the area.¹⁰ Finally, in some models we allow individual characteristics and social characteristics to interact in predicting perceived threat. This allows us to assess variation in the effect of predictors such as local area racial composition, depending on the race of the perceiver. Descriptive statistics and further description of the independent variables are shown in the appendix table available online at www.asanet.org/journals/spq.

The neighborhood level variables that we use to predict perceived crime risk are all based on zip-code level census data, with zip codes representing the smallest locational identifier for respondents' residences in the SEE survey. We used 1990 and 2000 census data and linear interpolation to estimate zip code characteristics for inter-censal years. Some interviews were conducted in 2001 and 2002, and we used 2000 census zip code data to approximate the census zip code conditions for these respondents. While census tracts are more often used as neighborhood equivalents than zip codes, we regard zip codes as an acceptable substitute in their absence. Zip codes are larger than census tracts—the average zip code in our sample

⁸ SEE questions about criminal victimization were asked prior to questions about job loss and insurance loss, thus avoiding the potential confound of dependency in initial starting points (Tversky and Kahneman 1974).

⁹ The data include only a measure of victimization in the past year. Including this measure in models estimating the risk of future victimization does not change the basic results or conclusions.

¹⁰ We use a measure of family poverty, rather than individual-level poverty rates, to avoid those local areas with high concentrations of college students who are often coded as "poor" despite their distinct socioeconomic profile (see Jargowsky 1997: 66-7). Using percentage poor instead produces similar results. We log our measure of population density to give it a more symmetric distribution since in its raw form it is highly positively skewed.

has an average population of about 25,000, compared to an average tract population of about 4,000—and may be thought to correspond to a large neighborhood area. To the extent that neighborhood boundaries are poorly measured, we would expect a conservative (downward) bias to coefficient estimates.¹¹

One of our major goals is to examine the extent to which there is bias in estimation of risk induced by the presence of racial minorities. Bias is the associated difference between perceived and actual risks. To generate this comparison, we estimate separate models to predict actual and perceived risk, respectively. We then compare the effects of the independent variables between the actual and perceived equations to draw conclusions about differences in how each predicts perceived and actual risk. Differences indicate the extent of bias in estimation associated with the corresponding independent variable.¹²

We estimate models using burglary and robbery outcomes with estimation and realization samples of SEE data for each. There is a larger sample size for burglary than for robbery because the robbery expectations question was not asked in the last three waves of the Survey of Economic Expectations. To increase the comparability of the time frame of expectations and realizations, we drop the first wave of the survey for realizations (asking about last year)

and the last wave of the survey for expectations (asking about the following year).

Models

As discussed above, we contrast coefficients across models that predict perceived estimates of risk with those from models predicting actual risk events (realizations). The comparison is facilitated by employing models that use the same functional form.

The realizations variable is a standard dichotomous indicator of having experienced an event (a robbery or burglary) in the prior year. To model this outcome, we use a logistic regression model in which individual and zip-code level variables predict experiences of victimization. Standard errors are adjusted to account for clustering of respondents within zip codes.¹³

Estimated risks are represented as numbers ranging from 0 to 100. To put the model into a similar metric for comparison to the logistic regression, we divide by 100 to put the dependent variable on a 0 to 1 scale, and then take the logit of the dependent variable. Before taking the logit, responses of 0 were coded to be .001; responses of 1 were recoded to be .999. Effectively, we assume estimated risks of 0 actually indicate a very small estimated risk; estimated risks of 1 indicate a very high estimated risk (but not certainty). If the respondents' estimated probability of the event is v , then the model is:

$$\text{Ln}(v/(1-v)) = a + b_1x_1 + b_2x_2 + \dots + b_kx_k + e \quad (1)$$

where the x values are the independent variables, the b values are their corresponding coefficients, and e is an error term. The resulting model with the logit-transformed dependent variable is estimated by ordinary least squares. This estimates a generalized linear model with a logit link, making it similar to logit models estimated using data that is grouped with

¹¹ We also examined models that tested for effects of racial composition at the much wider spatial scale of the metropolitan area. Studies working in the tradition of group threat have often found that attitudes toward minority groups in metropolitan areas, regions, or counties become more negative as the minority share of the population increases (see footnote 4). In our models with perceived risk of crime victimization as the outcome, however, we did not find statistically significant effects of metropolitan racial or economic composition on individual risk assessments. Individuals instead appear to respond more strongly to the characteristics of more proximate settings in forming estimates of risk.

¹² An alternative strategy might be to include measures of actual risk in models that predict perceived risk. That, however, would require measures of actual risk that are valid for individual neighborhoods. As we sketch in the literature review, however, the available neighborhood-level crime measures face serious biases that call into question their use when regarded as measures of actual crime rates.

¹³ Although multi-level models are often preferred for analyses of individuals nested within neighborhoods, the number of individuals per zip code in our data (median = 1) is too small for their use to be beneficial.

a proportion of “success” outcomes for each combination of values of the independent variables in the model (see Powers and Xie 2000, section 3.2). Because both models of realizations and models of expectations use a logit functional form, we are able to directly compare coefficients across models.

A final concern regarding the models is that zip code characteristics may be too highly intercorrelated to allow us to separate their effects in predicting risk estimates or realized risk events (multicollinearity). Fortunately, diagnostics for the most complete statistical models revealed little evidence of multicollinearity based on standard criteria.¹⁴

RESULTS

The results from models examining the contextual and individual factors affecting risk estimates and realizations are shown in Tables 2 and 3. We follow a similar progression of model specification across all dependent variables. First, we estimate a basic model with individual characteristics and percent black predicting actual and realized victimization risk. Second, we add a series of controls for zip-code population and housing characteristics that have been found in past research to predict local-area crime rates. Across all models, our primary interest is in assessing how local area racial composition predicts estimated and realized risks, and how these effects are altered by including other nonracial contextual characteristics as predictors.¹⁵

¹⁴ We calculated variance inflation factors (VIF) for all independent variables in the second expected and realized model in tables 3 and 4 (see Chatterjee and Hadi 2006, section 9.4). A VIF of 10 or greater for a variable is often taken to indicate a possible multicollinearity problem. In our models, no variable had a VIF of greater than 4.

¹⁵ We also examined the relationship between local area percent black and our other two cases of risk—job loss and being without health insurance—to investigate the possibility that racial composition is associated with a general elevation in the expectation of adverse events. We find no systematic relationship between percent black and either of these risk estimates.

Burglary

Table 2 shows the results for the burglary outcome. The left two columns present coefficients for predictors of expectations of risk; the right two columns present coefficients for predictors of realized risk (e.g., actual victimization). The effects of local area characteristics on expected and realized risks are shown in the top panels of the table.

Initially considering the racial composition main effect, we see in model 1 that among white respondents zip code percent black is associated with both expected and realized burglary rates.¹⁶ Once nonracial characteristics of the area are included in model 2, however, we find diverging effects of racial composition: zip code percent black remains a significant predictor of estimated burglary risk but drops close to zero and becomes statistically insignificant in predicting actual burglary incidents.¹⁷ Percent Hispanic is likewise significantly associated with estimated risk, but not with realized risk, when other zip code characteristics are controlled.

Though racial composition is not related to actual victimization rates, other contextual characteristics are. Local area economic conditions—in particular, per capita income levels—are strongly related to burglary rates, with respondents in poorer neighborhoods at higher risk. Likewise, greater population density is associated with higher levels of burglary victimization. Low income and dense areas

¹⁶ The models include interaction terms between zip code percent black and individual race (white/nonwhite) to allow for the possibility that zip code percent black has different slopes on perceived and realized risk depending on the race of the respondent. Zip code percent Hispanic and individual race are also interacted. Because whites are the race reference group (white=0, nonwhite=1), the main effect term for percent black and percent Hispanic then indicates how these are related to the outcome for white respondents.

¹⁷ We performed a cross-model significance test (Wald test) of no significant difference in the slope of percent black in the estimated and realized models based on a jointly estimated covariance matrix, which accounts for estimated covariances between coefficients (see Wessie 1999). The test rejects the null hypothesis at the $p < .1$ level.

Table 2. Models of Estimated Risk and Realized Incidents of Burglary Victimization

	Estimated		Realized	
	Model 1	Model 2	Model 1	Model 2
Local Area Racial Composition (and Interactions with Race of Respondent)				
% Zip code black	0.0140*** (0.0025)	0.0120*** (0.0031)	0.0116* (0.0048)	0.0023 (0.0057)
% Black × Nonwhite	−0.0087* (0.0040)	−0.0085* (0.0039)	0.0019 (0.0065)	0.0010 (0.0064)
% Zip code Hispanic	0.0131*** (0.0028)	0.0079* (0.0038)	0.0121* (0.0053)	0.0031 (0.0068)
% Hispanic × Nonwhite	−0.0015 (0.0045)	−0.0011 (0.0044)	−0.0021 (0.0074)	−0.0035 (0.0072)
Local Area Economic Conditions				
Zip code family poverty rate		−0.0013 (0.0071)		0.0131 (0.0120)
Zip code per capita income (in 1000's of year 2000 dollars)		−0.0147*** (0.0044)		−0.0411** (0.0148)
Local Area Population and Housing Characteristics				
% Zip code male 15 to 24		−0.0114 (0.0089)		−0.0168 (0.0215)
% Zip code housing units vacant		−0.0077* (0.0038)		0.0136 (0.0076)
% Zip code foreign born		0.0054 (0.0049)		0.0018 (0.0081)
Log of zip code population density (Persons per sq. km.)		0.0344 (0.0204)		0.1180** (0.0438)
Residence in metropolitan area (1=yes)		0.0047 (0.0716)		−0.2400 (0.1790)
Respondent Characteristics				
Respondent nonwhite (1=yes)	0.0045 (0.1270)	−0.0143 (0.1270)	0.2150 (0.2430)	0.2690 (0.2370)
Respondent family income (in thousands)	0.0002 (0.0002)	0.0003 (0.0002)	−0.0011 (0.0014)	−0.0001 (0.0010)
Age (years)	−0.0160*** (0.0018)	−0.0155*** (0.0018)	−0.0123** (0.0042)	−0.0117** (0.0043)
Gender (1=male)	−0.0258 (0.0563)	−0.0328 (0.0563)	0.1510 (0.1260)	0.1390 (0.1250)
Respondent Education (reference is No High School Degree)				
High school degree	−0.0155 (0.1320)	−0.0252 (0.1320)	−0.4150 (0.2240)	−0.3730 (0.2240)
Some college	0.1050 (0.1280)	0.0946 (0.1310)	−0.3910 (0.2170)	−0.3320 (0.2220)
College degree or more	−0.0207 (0.1180)	−0.0174 (0.1210)	−0.4900* (0.1970)	−0.3690 (0.1970)
Constant	−2.3630*** (0.1670)	−2.1460*** (0.2280)	−2.5790*** (0.3400)	−2.6670*** (0.5200)
N	7364	7363	7158	7158

Note: Standard errors in parentheses. Models also include 13 dummy variables to indicate year of the survey. Standard errors adjusted for clustering on zip code.
* $p < .05$; ** $p < .01$; *** $p < .001$.

thus present the greatest risk of burglary, irrespective of their racial composition. The effect of racial composition disappears simply with the inclusion of controls for the local area economic conditions.

These results point to an interesting paradox: White respondents' estimates of victimization risk are heavily influenced by racial composition; actual risks, by contrast, are not affected by racial composition, but rather by the neighborhood's per capita income level and the overall population density. Respondents' estimates of risk take some account of these additional contextual influences. Both per capita income and population density demonstrate some effect on estimates of risk in the expected direction.¹⁸ Note, however, that the coefficients for these variables are one-third to one-fourth the size of those for actual burglary incidents. Thus, while respondents do appear to notice a range of demographic characteristics in forming their estimates of risk, the weight they place on the various characteristics differs from models predicting actual victimization. In particular, racial composition stands out as a salient marker for estimating risk, despite its limited predictive value. In general, the cues individuals rely upon to generate estimates of risk do not map closely onto the factors associated with actual risk.

Does the effect of racial composition differ depending on the race of the respondent? We explore this possibility by including interaction terms between racial composition and race of respondent. Due to small sample sizes for minority respondents, we pool nonwhite respondents

into a single category.¹⁹ The interaction term between percentage black and race of respondent (1 = nonwhite) is negative and statistically significant; when added to the main effect, it implies that zip code percent black does not drive perceptions of burglary risk for minority respondents as it does for white respondents. Figure 3 illustrates patterns of estimated and realized burglary risk against zip code percent black, based on the second model in Table 2. For both estimated and realized risk, two lines are present, one for white and one for nonwhite respondents. The shaded areas are predictive interval regions for the estimates of white respondents. The results illustrate that, as the percentage of black residents in a local area increases, the perception of burglary risk among white respondents increases accordingly. Indeed, the diverging lines at the top of Figure 3 illustrate the strong effect of racial composition in driving estimates of risk among whites; the line for nonwhites, by contrast, remains flatter across the distribution of neighborhood racial composition.²⁰

Unlike estimates of risk, actual rates of burglary victimization do not vary according to racial composition. The relatively flat parallel lines at the bottom of Figure 3 illustrate the lack of association between racial composition and victimization rates for respondents of any race. Where the actual rate of burglary victimization is driven overwhelmingly by the economic characteristics of the local area (per capita income), perceptions of white respondents are much more strongly linked to the racial composition of the neighborhood.

Robbery

Turning from burglary to robbery, Table 3 provides coefficients from a sequence of models comparable to those in Table 2, revealing a similar pattern of results. In models both with and without controls for zip

¹⁸ Respondents also appear influenced by the percent of vacant housing units in their neighborhood, though this coefficient is not in the expected direction. The results suggest that zip code areas with a greater proportion of units vacant are associated with lower estimated risks of burglary. It may be the case here that our measure of vacant units is picking up new housing development rather than abandoned dwellings.

¹⁹ The results are consistent when we focus on black respondents only, but statistical power to estimate the racial difference is further reduced. We did not find statistically significant interactions between Hispanic and zip code percentage Hispanic, although this may be in part due to the small number of Hispanic respondents in the survey.

²⁰ Consistent with this conclusion, a significance test does not reject the hypothesis that in model 2 the slope of percent black on black perceptions of victimization risk is zero. The same holds for the models of robbery presented below (not shown; $p > .1$).

Table 3. Models of Estimated Risk and Realized Incidents of Robbery Victimization

	Estimated		Realized	
	Model 1	Model 2	Model 1	Model 2
Local Area Racial Composition (and Interactions with Respondent Race)				
% Zip code black	0.0156*** (0.0028)	0.0157*** (0.0033)	0.0213** (0.0080)	0.0131 (0.0092)
% Black × Nonwhite	-0.0118** (0.0043)	-0.0116** (0.0043)	-0.0178 (0.0112)	-0.0182 (0.0110)
% Zip code Hispanic	0.0167*** (0.0030)	0.0133*** (0.0040)	0.0177 (0.0098)	0.0037 (0.0166)
% Hispanic × Nonwhite	0.0001 (0.0048)	0.0016 (0.0048)	-0.0204 (0.0138)	-0.0206 (0.0142)
Local Area Economic Conditions				
Zip code family poverty rate		-0.0087 (0.0066)		0.0291 (0.0213)
Zip code per capita income (in 1000's of year 2000 dollars)		-0.0040 (0.0053)		0.0000 (0.0174)
Local Area Population and Housing Characteristics				
% Zip code male 15 to 24		-0.0252* (0.0116)		-0.0525 (0.0441)
% Zip code housing units vacant		-0.0056 (0.0042)		-0.0136 (0.0196)
% Zip code foreign born		0.0033 (0.0055)		0.0142 (0.0236)
Log of zip code population density (Persons per sq. km.)		0.0773*** (0.0233)		0.1270 (0.0898)
Residence in metropolitan area (1=yes)		0.0104 (0.0800)		-0.3750 (0.3880)
Respondent Characteristics				
Respondent nonwhite (1=yes)	0.1680 (0.1440)	0.1180 (0.1440)	1.3640** (0.4410)	1.3230** (0.4400)
Respondent family income	0.0007* (0.0003)	0.0005* (0.0002)	-0.0039 (0.0041)	-0.0036 (0.0041)
Age (years)	-0.0158*** (0.0020)	-0.0158*** (0.0020)	-0.0214* (0.0087)	-0.0214* (0.0088)
Gender (1=male)	-0.3790*** (0.0592)	-0.3840*** (0.0590)	-0.2640 (0.2710)	-0.2760 (0.2700)
High school degree	0.0629 (0.1470)	0.0239 (0.1470)	-0.5780 (0.5540)	-0.5850 (0.5540)
Some college	0.2040 (0.1400)	0.1320 (0.1410)	-0.1230 (0.4470)	-0.1790 (0.4560)
College degree or more	0.0630 (0.1330)	-0.0321 (0.1350)	-0.1870 (0.4130)	-0.2340 (0.4190)
Constant	-2.5480*** (0.1800)	-2.5730*** (0.2540)	-4.3310*** (0.8180)	-4.7840*** (1.1760)
<i>N</i>	5904	5904	5102	5102

Note: Standard errors in parentheses. All models also include 10 dummy variables to indicate year of the survey. Standard errors adjusted for clustering on zip code.

* $p < .05$; ** $p < .01$; *** $p < .001$.

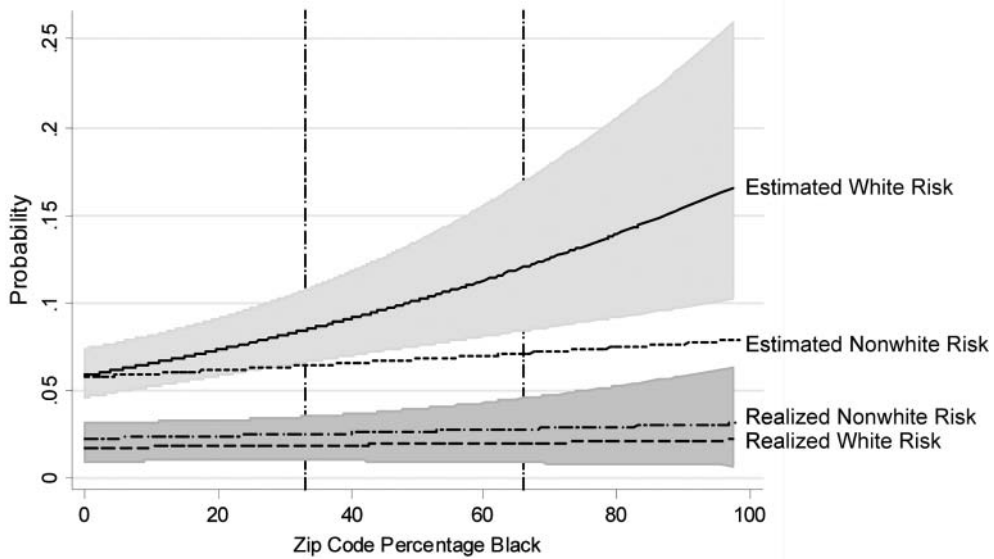


Figure 3. Estimated and Realized Burglary Risk and Zip Percentage Black. Shaded areas are 95% prediction intervals for whites, based on full model (model 2). The dotted vertical lines separate three ranges of zip code percent black, with sample sizes as follows: Range 1 (0-33% black): N white (estimated/realized) = 5866/5364; N nonwhite = 902/876; Range 2 (34-66% black): N white = 232/246; N nonwhite = 189/185; Range 3 (67-100% black): N white = 48/51; N nonwhite = 128/124. As sample sizes grow smaller, estimates are based more on extrapolation.

code population characteristics, expectations of victimization among whites are strongly associated with local area racial composition. The percentage of black residents is strongly associated with elevated estimates of risk of robbery. Like for burglary, the interaction between percent black and race of the respondent shows a large and statistically significant negative effect. Only among white respondents, therefore, is there a significant positive relationship between zip code percentage black and estimated victimization risk.

Robbery realizations, on the other hand, are not significantly related to zip code racial composition once other population characteristics are accounted for. In fact, none of our zip-code characteristics are statistically significant in the full model. The major reason for this has to do with the limits of our data: Because robbery is an infrequent event (occurring to only 1.2 percent of our sample per year on average), there are few robbery events in our realization sample. Correspondingly, the model produces imprecise

estimates of the partial effects of most predictors of robbery.²¹ In addition, the insignificance of local area predictors of robberies may reflect the fact that robberies (unlike burglaries) can occur outside of one's neighborhood of residence, making characteristics of the zip code context less predictive of robbery events.

Figure 4 graphs the estimated risk of robbery and actual rates of robbery as a function of zip code percent black. For white respondents, the extent of overestimation of perceived risk of robbery increases directly as zip code percent black increases, diverging from the flatter estimates of nonwhite respondents. By contrast, realized rates of robbery appear relatively flat for both whites and nonwhites, only weakly related to neighborhood racial composition.

²¹ Because of the small number of robbery incidents, cross-model tests indicate that the hypothesis of no difference in the percentage black slope between the estimation and realization robbery model cannot be rejected.

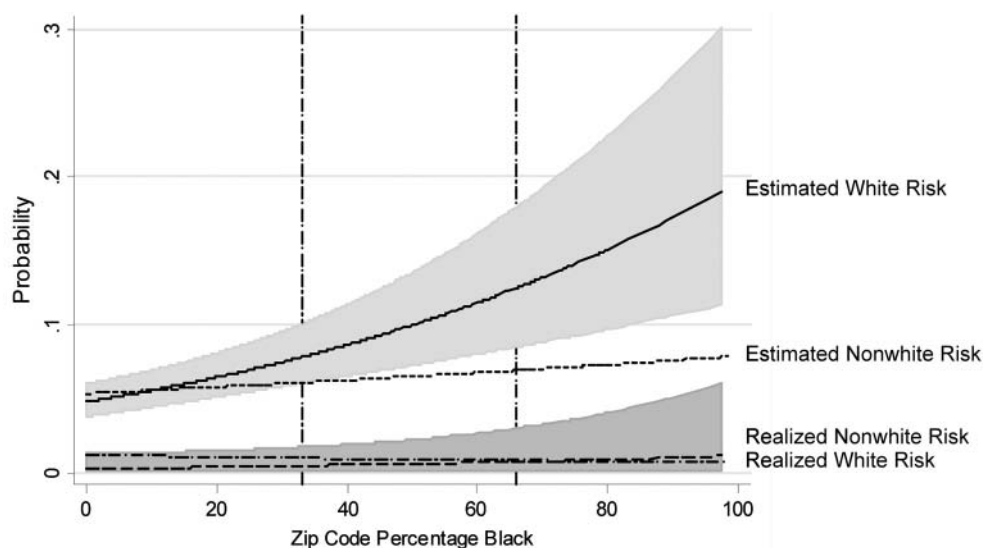


Figure 4. Estimated and Realized Robbery Risk and Zip Percentage Black. Shaded areas are 95% prediction intervals for whites. From full model (model 2). *N*'s shown are estimated/realized for three ranges of zip code percent black. The dotted vertical lines separate three ranges of zip code percent black, with sample sizes as follows: Range 1 (0-33% black): *N* white (estimated/realized) = 4735/4043; *N* nonwhite = 695/600; Range 2 (34-66% black): *N* white = 175/158; *N* nonwhite = 152/132; Range 3 (67-100% black): *N* white = 43/40; *N* nonwhite = 104/88. As sample sizes grow smaller, estimates are based more on extrapolation.

Racial Cues and Estimates of Risk

In analyzing models of both burglary and robbery, we find that white respondents rely heavily on cues about racial context in evaluating levels of personal risk. Is it the case, then, that respondents are irrational in evaluating the range of risk factors associated with criminal victimization? We hesitate to draw such a broad conclusion. Note that in model 1 of the analyses for both burglary and robbery, the coefficient for percent black is roughly comparable in estimates of both expected and realized risk. If respondents had access to no additional local area information, then they would indeed place appropriate weight on the relevance of racial composition in forming their estimates of risk. Where estimates appear to falter, however, is in taking account of other relevant contextual cues. Indeed, racial composition is not the only neighborhood characteristic that can be observed by residents. Basic information about the economic condition of the neighborhood and its population density is discernable and

widely recognized by neighborhood residents (Krysan et al. 2007; Pattillo 2008)—especially for individuals actually living in the neighborhood—and each of these factors is directly relevant to the actual risk of criminal victimization. Unfortunately, respondents appear to systematically downplay the importance of this additional contextual information, instead placing great emphasis on racial composition as their primary guide to assessing risk. Where racial composition may be an adequate proxy in the absence of other contextual information, it provides only a poor representation of risk once other observable neighborhood conditions are taken into account.

Looking back to our model of crime-risk estimation, these results provide support for the concept of risk amplification: Respondents notice and utilize relevant contextual information in forming their estimates of risk, but do so in a way that amplifies the relevance of certain factors (e.g., racial composition) while downplaying the relevance of others (e.g., economic conditions). Resulting

estimates exaggerate the level of risk in black neighborhoods, particularly those in working-class or middle-class neighborhoods, where levels of risk are substantially lower relative to those at the bottom end of the income distribution. Strong associations between race and crime appear to lead to a privileging of this noisy proxy for risk, while the true culprits (economic conditions) receive far less emphasis.

These results are particularly interesting in light of the fact that comments about “neighborhood” or “where you live” were never mentioned in the survey. Respondents were simply asked to evaluate their risk of these negative events without regard to location. This is one distinguishing feature of our study relative to prior investigations of the associations between perceived levels of neighborhood crime and neighborhood racial composition. It is especially notable that the robbery estimates are so strongly associated with zip code characteristics, despite the fact that robberies can occur anywhere. The results provide striking evidence of the racialization of burglary and robbery risk. The mental association of race and crime appears to be sufficiently powerful as to override most other cues in the social environment that may be linked to risks of victimization.

In addition, we point out two facts that we suspect make our results somewhat conservative. First, neighborhood racial composition measures are based on the local area in which respondents are actually living, not on prospective neighborhoods they are visiting or considering briefly. Respondents thus should have relatively strong familiarity upon which to base judgments about neighborhood conditions and neighborhood crime rates, likely resulting in less heavy reliance on easily visible characteristics (like racial composition) in evaluations of local factors that may affect their victimization risk. Prospective residents or businesses considering a new neighborhood may place even greater weight on racial cues in evaluating levels of risk than what we find here. Second, it is likely that white respondents holding the strongest associations between race and crime are likely to migrate

away from highly black areas. The net effect of this migration is to suppress the measured association between zip code percent black and perceptions of crime. If individuals were randomly assigned to their neighborhood of residence, it is likely that the association of zip code race and perceived risk of crime would be stronger than what we find here.

As a final comment on the discrepancy between estimated and realized burglary risks, it is important to note that racial composition is not the only factor driving the exaggeration of risk. While the extent of overestimation of victimization risk increases steadily as the percentage of blacks in the local area increases, Figures 3 and 4 also show a large gap between estimated and realized crime risks in all-white areas (when percent black = 0). While racial composition clearly demonstrates a large and significant effect on perceived risk, other factors not linked to neighborhood conditions also play an important role. Prominent media representations of actual and fictional crime events, for example, are likely to shape respondents' perception of crime and their assessments of risk in ways unrelated to local area conditions (see Gilliam and Iyengar 2000). While such media effects may themselves depend on heavily racialized imagery (Entman 1990), these processes will not be captured by zip code racial composition.

While our model cannot capture all factors related to the exaggeration of risk, it does identify the important influence of local area conditions. Further, of the many observable characteristics about neighborhoods that may be related to crime, we observe a systematic privileging of racial composition—and a systematic downplaying of economic conditions—in forming estimates of risk. Respondents selectively attend to available contextual information in ways that lead to exaggerated perceptions of the risk of crime.

DISCUSSION

Unlike estimates of the risk of job loss or the absence of health insurance, which are remarkably accurate, respondents significantly

overestimate their risks of being the victim of crime. The results of our analysis support the idea that perceptions of burglary and robbery risk are strongly triggered by the presence of racial minorities in the local area, in particular African Americans. These strong associations between race and crime, however, do not correspond to actual risks. While there is a zero-order correlation between racial composition and some types of crime, respondents tend to exaggerate this relationship while ignoring other social cues (i.e., economic conditions) which are far more predictive of crime. The importance of percent black as a cue for perceived risk, however, appears to hold primarily for white respondents. As a result, white respondents overestimate their risk of crime victimization more than twice as much in heavily black zip codes relative to areas with few black residents.

This bias in risk perceptions represents a systematic distortion in associations between neighborhood racial composition and crime. While we cannot identify the precise source of these associations, the results are consistent with the influence of widespread cultural stereotypes associating blacks with crime (Smith 1991; Devine 1989) as well as distortions in media coverage, which tends to exaggerate the amount of violent crime and the degree to which violent crime is committed by blacks (Entman 1990; Dixon and Linz 2000). Although the mechanisms underlying these results cannot be observed directly, we believe the evidence strongly points toward stereotype amplification as the explanation of these patterns. Future research combining measures of perceived and realized risk with individuals' stereotypic associations may be able to establish this relationship more directly.

The case of criminal victimization provides one important illustration of the influence of social context on risk perceptions. We suspect that a similar process of amplification of perceived risks is likely to occur for events that have three characteristics shared with criminal victimization. First, the risk event is strongly linked in public understandings to stereotypes of social groups. Crime, for instance, is strongly linked in the public consciousness to

race and gender. Second, social categories linked to stereotypes are highly visible in the contexts in which risks are evaluated. The social contexts of neighborhoods, for example, are often race-typed in public understanding. Third, there is low specific knowledge and personal experience with the risk event. Most knowledge of crime comes from sources other than personal experience, most notably the mass media. As these conditions hold more perfectly, we expect that the prevailing social context will cue stereotypic associations that increasingly overwhelm other salient risk indicators, with a resulting exaggeration in perceptions of stereotype-linked risks.

These three primary conditions are present to a significant degree in a number of consequential decision contexts. In employment situations, for example, employers must regularly consider the risks associated with prospective hires (e.g., poor performance, theft, threatening behavior). Previous research has shown that employers hold strong stereotypes about the talents and liabilities of workers on the basis of their race, gender, and social background (e.g., Kirschenman and Neckerman 1991; Ridgeway and Correll 2004). In the face of limited information about a given candidate, race, gender, and neighborhood often become salient markers for levels of risk, potentially leading to overestimates of stereotype-linked risks among well-qualified applicants from stereotyped groups (e.g., Pager, Western, and Bonikowski 2009). Similar processes of risk amplification may contribute to racial disparities observed in decisions to rent an apartment, authorize a loan, or make an arrest (Yinger 1995; Turner and Skidmore 1999; Sampson and Lauritsen 1997). Further investigation into how individuals assign weights to information in risk evaluation and under what circumstances these weights become distorted may then do much to advance our understanding of the processes that produce discrimination against disadvantaged groups.

The amplification framework may likewise be extended to other contexts in which perceptions of risk are filtered through a distorted cultural lens. Perceptions of risks to health

and well-being, for example, illustrate some of the ways that cultural fears of the unknown can result in elevated perceptions of risk from unlikely events: Americans report greater concern over anthrax (associated with zero deaths per year) than influenza (associated with more than a quarter-million deaths per year), and perceive greater risks associated with terrorist action than from the threat of global warming (Gilbert 2006). The amplification of risks associated with biochemical warfare or terrorism are likely fueled in part by their underlying associations with threatening foreign cultural origins. While each of these examples includes its own unique circumstances, it is useful to consider the common underlying process by which risk estimates are shaped by their social and cultural context.

Future research would contribute substantially to our understanding of the sociology of risk by further clarifying the scope conditions of the amplification framework, to better understand when and how risks—from everyday to rare events—are influenced by their social context. The present research suggests that in some cases (e.g., job loss, absence of health insurance), individuals are extremely accurate in predicting risk. In others, by contrast (e.g., criminal victimization), risks are substantially distorted by the social contexts in which they are assessed. Contrary to models of statistical discrimination—which generally take risks to be correctly perceived—this evidence suggests that, at least for some events, stereotype-consistent risks may be systematically overestimated. These results call into question the assumed efficiency of social heuristics as guides for decision-making, given that perceptions may be vulnerable to significant forms of bias.

The ability to notice and make sense of our social environment is not without limits. Where in many cases individuals may accurately gauge the relevance of their surroundings for everyday decision-making (e.g., noticing an overcast sky; responding to congestion on the highway), decisions influenced by stereotypic associations appear more vulnerable to distortion. In the case considered here, amplification leads to the privileging of certain cues (race) while

others (income) are ignored. Understanding the circumstances in which risk estimates are improved or distorted by information about the social context would do much to increase both the efficiency and equity of decision-making under conditions of uncertainty.

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