THE USE OF INTENTIONS DATA TO PREDICT BEHAVIOR: A BEST-CASE ANALYSIS

Charles P. Manski
Department of Economics
and
Institute for Research on Poverty
University of Wisconsin-Madison

Revised: October, 1989

This work is supported by National Science Foundation Grant SES-8808276 and by a grant from the U.S. Department of Health and Human Services to the Institute for Research on Poverty. Some of the ideas developed here originated in joint research with Daniel Nagin, undertaken around 1980. Our note "Behavioral Intentions and Revealed Preferences" was circulated informally at that time. More recently, I have benefited from useful discussions with Rob Mars, Betty Thomson, and Jim Walker and from the opportunity to present this material in seminars at the University of Wisconsin Center for Demography and Ecology and at the National Bureau of Economic Research.

Key Words: intentions, prediction of behavior, survey design
Abstract

In surveys individuals are routinely asked to predict their future behavior, that is, to state their intentions. This paper studies the relationship between stated intentions and subsequent behavior under the "best-case" hypothesis that individuals have rational expectations and that their responses to intentions questions are best predictions of their future behavior. The objective is to place an upper bound on the behavioral information contained in intentions data and to determine whether prevailing approaches to the analysis of intentions data respect the bound. The analysis focuses on the simplest form of intentions questions, those that call for yes/no predictions of binary outcomes. The paper also discusses "forced-choice" questions, which are distinct from but are sometimes confused with intentions questions.

A primary lesson is that not too much should be expected of intentions data. It is shown that intentions data bound but do not identify the probability that a person will behave in a given way. The derived bounds are nonparametrically estimable and may be used to test the best-case hypothesis. Contrary to assertions in the literature, there is no reason to think that individual-level differences between intentions and behavior should "average-out" in the aggregate.
"INTENTIONS implies little more than what one has in mind to do or bring about," Webster's Eighth New Collegiate Dictionary (1985, p. 629)

1. INTRODUCTION

In surveys individuals are routinely asked to predict their future behavior, that is, to state their intentions. The fertility question asked female respondents in the June 1987 Supplement to the Current Population Survey (CPS) is an example:

Looking ahead, do you expect to have any (more) children?
Yes No Uncertain
(U.S. Bureau of the Census, 1988)

Another example is the set of schooling-work questions asked in fall 1973 of respondents to the National Longitudinal Study of the High School Class of 1972 (NLS72).

What do you expect to be doing in October 1974?
(Circle one number on each line)
Expect to Do not expect to
be doing be doing
Working for pay at a full-time
or part-time job
Taking vocational or technical
courses at any kind of
school or college
Taking academic courses at a
two-year or four-year college
On active duty in the Armed
Forces (or service academy)
HOMEMAKER

1 2
1 2
1 2
1 2

(Riccobono et al., 1981)
This paper studies the relationship between stated intentions and subsequent behavior under the "best-case" hypothesis that individuals have rational expectations and that their responses to intentions questions are best predictions of their future behavior. I do not assert that this best-case hypothesis is necessarily realistic. My objective is to place an upper bound on the behavioral information contained in intentions data and to determine whether prevailing approaches to the analysis of intentions data respect the bound.

The analysis focusses on the simplest form of intentions questions, those that call for yes/no predictions of binary outcomes. The NLS72 schooling-work questions are an example. There is some discussion of questions allowing more refined responses, such as the yes/no/uncertain response sought in the CPS fertility question, and of questions asking for the probability that a binary outcome will occur. There is also discussion of forced-choice questions, which are distinct from but are sometimes confused with intentions questions. This paper does not examine questions seeking predictions of quantitative outcomes, such as the CPS fertility supplement question asking "How many more do you expect to have?"

Even within the restricted world of best-case response to yes/no questions about binary behavior, the interpretation of intentions data requires care. A primary lesson is that one should not expect too much of such data. Some of the literature interprets empirical divergences between intentions and behavior
as evidence that individuals are poor predictors of their own future behavior. This conclusion is unwarranted.

Even if individuals have rational expectations and stated intentions are best predictions of behavior, intentions and behavior need not coincide. The two may diverge whenever the information available to the respondent at the time of the survey is more limited than the information he or she will possess at the later time when behavior is determined. There is, moreover, no reason to believe that individual-level differences between intentions and behavior "average-out" in the aggregates. Suppose, for example, that all of the NLS72 respondents say that they expect to be working in October 1974. Suppose that only 50 percent subsequently do so. This pattern of responses is consistent with the best-case hypothesis.

The foregoing negative findings notwithstanding, intentions data do potentially convey information about behavior. The constructive contribution of this paper is to show that, under the best-case hypothesis, intentions data bound the probability that an individual will behave in a given way. Moreover, the bounds reported here are nonparametrically estimable.

The standard practice has been to measure the information in intentions data by the correlation between intentions and behavior or by the explanatory power of intentions in a regression of the behavioral outcome on intentions and other variables. But correlations and regression coefficients do not
appropriately express the information content of intentions data. Probability bounds do.

Section 2 provides background on the analysis of intentions data, commenting on the different paths taken by two of the social sciences, and calling attention to previous research related to that reported here. The main findings are developed in Section 3, which shows that intentions data bound but do not identify the probability that a person will behave in a given way. Section 4 applies these bounds to the problem of testing the best-case hypotheses and presents some mixed empirical evidence. Section 5 discusses "forced-choice" questions. Section 6 offers conclusions.

Although the substantive concern of this paper is the use of intentions data, most of the analysis applies to a larger class of prediction questions asked in surveys. Individuals are often asked to make a point prediction of some future binary event, not necessarily their own future behavior. For example, economists are often asked to predict whether the unemployment rate will rise or fall. The analysis of Sections 3 and 4 applies to such questions. Only the work of Section 5 is specific to questions regarding the respondent's own behavior.
2. Background

Responses to fertility questions such as that in the CPS have been used to predict fertility for over fifty years. Henderson and Placek (1981) review the extensive literature. Data on voting-intentions have been used to predict American election outcomes since the early 1900s. See Turner and Martin (1984). Surveys of buying-intentions have been used to predict consumer purchase behavior since at least the mid 1940s. See Juster (1966). The long history of intentions surveys notwithstanding, social scientists seeking to predict behavior continue to differ sharply in their interpretation of stated intentions and in the use they make of such data. It is particularly intriguing to contrast the perspectives of social psychologists and economists.

2.1. Social Psychology

Social psychologists take intentions very seriously. They suppose that intention is a mental state that causally precedes behavior and that can be elicited through questionnaires or interviews. The enormously influential work of Fishbein and Ajzen (1975) makes "behavioral intentions" the intermediate variable in a path model wherein (1) intentions are determined by attitudes and social norms and (2) behavior is determined by intentions alone.
According to Ajzen and Fishbein (1980), a person's behavioral intention is his subjective probability that the behavior of interest will occur. (They refer to the response to a yes/no intentions question as "choice intention.") It seems, however, that social psychologists do not use the term "subjective probability" as a statistician would. Ajzen and Fishbein (1980) state "we are claiming that intentions should always predict behavior, provided that the measure of intention corresponds to the behavioral criterion and that the intention has not changed prior to performance of the behavior" (page 50). In their well-known review of attitudinal research, Schuman and Johnson (1976) write that the Fishbein/Ajzen model implies that "the correlation between behavioral intention and behavior should approach 1.0, provided that the focal behavior is the same in both cases and that nothing intervenes to alter the intention" (page 172). It is difficult to reconcile these statements with the idea that behavioral intention is a subjective probability, unless that probability is always zero or one.

In practice, social psychologists typically measure intention on some nominal scale (e.g. Ajzen and Fishbein, 1980, recommend a seven point scale whose verbally described responses range from "likely" to "unlikely") and report the correlation between this measure and the behavioral outcome. It is usually found that the correlation is positive but well below unity. See, for example, Schuman and Johnson (1976) and Davidson and Jaccard (1979). Social psychologists have reacted by generalizing the Fishbein-
Ajzen model while maintaining its basic path structure. Recent contributions to the literature posit path models wherein (1) intentions are determined by attitudes, social norms, and objective circumstances and (2) behavior is determined by intentions, attitudes, norms, and circumstances. See, for example, Davidson and Jaccard (1979), Liska (1984), and Ritter (1988).

2.2. Economics

Economists, observing the frequency of divergence between stated intentions and subsequent behavior, generally ignore intentions data. The dominant view is deep skepticism about the credibility of subjective statements of any kind. Early in their careers, economists are taught to believe only what people do, not what they say. The practice is to predict future behavior by using data on past behavior, filtered through econometric models of decision making. See, for example, the exposition of econometric choice analysis and the predictions of schooling-work behavior, based on NLS72 data, reported in Manski and Wise (1983).

The economics discipline has not always been so closed to the use of intentions data to predict behavior. From the mid 1950s through the mid 1960s, analysis of consumer buying-intentions was close to a mainstream activity, engaging the attention of such figures as Thomas Juster, George Katona, Eva Mueller, Arthur Okun, and James Tobin. Juster (1964, 1966) reviews this literature. He also makes original contributions of particular interest.
Considering the problem in which the behavior of interest is a binary purchase decision (buy or not buy) and the intentions question is also binary (intend to buy or not intend to buy), Juster(1966) wrote "Consumers reporting that they 'intend to buy A within X months' can be thought of as saying that the probability of their purchasing A within X months is high enough so that some form of 'yes' answer is more accurate than a 'no' answer" (page 664). Thus, he hypothesized that a consumer facing an intention question responds as would a statistician asked to make a best point prediction of a future event. Working from this hypothesis, Juster concluded that it would be more informative to ask consumers for their purchase probabilities than for their buying intentions. He presented empirical evidence that stated purchase probabilities are better predictors of subsequent behavior than are yes/no intentions data.

For whatever reason, economists subsequently lost interest in the analysis of intentions data, leaving the study of buying intentions to market researchers such as Morrison(1979), Urban and Hauser(1980), and most recently, Jamieson and Bass(1989). It is revealing that the recent National Academy of Sciences Panel on Survey Measurement of Subjective Phenomena had no economist as a member of the panel and cited almost no economics literature in its report. See Turner and Martin(1984).
1. BOUNDS ON BEHAVIOR IMPLIED BY INTENTIONS DATA

3.1. The Survey Question and the Best-Case Response

Suppose that a person is asked to make a point prediction of some binary choice. That is, a yes/no answer is requested, as in each of the NLS72 schooling-work questions. Let \( i \) and \( y \) be zero-one indicator variables denoting the survey response and future behavior respectively. Thus \( i = 1 \) if the person responds "yes" to the intentions question and \( y = 1 \) if his behavior turns out to satisfy the property of interest.

To form his response, a person with rational expectations would begin by recognizing that his future behavior will depend in part on conditions known to him at the time of the survey and in part on events that have not yet occurred. Let \( s \) denote the information available to the respondent at the time of the survey. Let \( z \) denote the events that have not yet occurred but which will affect his future behavior. Thus \( z \) represents uncertainty which will be resolved between the time of the survey and the time at which the behavior is determined. The behavior \( y \) is a function of the pair \((s,z)\) and so may be written \( y(s,z) \).

Let \( P(z|s) \) denote the objective probability distribution of \( z \) conditional on \( s \). Let \( P(y|s) \) denote the objective distribution of \( y \) conditional on \( s \). The event \( y = 1 \) occurs if and only if the realization of \( z \) is such that \( y(s,z) = 1 \). Hence
The content of the rational-expectations hypothesis is that, at the time of the survey, the respondent knows \( y(s,\ast) \) and \( P_i|s \); hence he knows \( P(y=1|s) \). It does not suffice for the respondent to have a subjective distribution for \( z \), from which he derives a subjective distribution for \( y \). Rational-expectations assumes knowledge of the actual stochastic process generating \( z \).

The second part of the best-case hypothesis is that the respondent states his best point prediction of his behavior. The best prediction necessarily depends on the losses the respondent associates with the two possible prediction errors \((i=0, y=1)\) and \((i=1, y=0)\). These losses may be influenced by the wording of the intentions question; for example, the respondent may interpret differently questions that ask what he "expects," "intends," or "is likely" to do. Whatever the loss function, however, the intentions response satisfies the condition

\[
\begin{align*}
(2) \quad i = 1 & \Rightarrow P(y=1|s) \geq \pi \\
i = 0 & \Rightarrow P(y=1|s) \leq \pi ,
\end{align*}
\]

where the threshold-probability \( \pi \) depends on the loss function.
3.2. Prediction of Individual Behavior Conditional on Intentions

Now consider a researcher who wishes to use intentions data to predict the behavior of some respondent. The researcher observes the intentions response \(i\). Continuing the theme of a best-case analysis, assume the researcher knows that \(i\) satisfies (2). Moreover, assume that \(x\) is the same for all respondents and that the researcher knows what \(x\) is.

The researcher may observe only a subset of the information \(s\) available to the respondent. Let \(x\) denote the observed component of \(s\). Suppose that the researcher wishes to predict the behavior conditional on the observed variables \(x\) and \(i\). Then he would like to learn the probability \(P(y=1|x, i)\). Intentions data do not identify \(P(y=1|x, i)\). They do, however, imply a bound.

Let \(P_x|s_i\) denote the probability distribution of \(s\) conditional on the observed pair \((x, i)\). It is the case that

\[
(3) \quad P(y=1|x, i) = \int P(y=1|s) dP_x|s_i.
\]

It follows directly from this and from (2) that

\[
(4) \quad P(y=1|x, i=0) \leq P(y=1|x, i) \leq P(y=1|x, i=1).
\]

This bound expresses all the information about behavior contained in the intentions data. Note that the position of the bound varies with \(i\) but not with \(x\).
The foregoing implies that familiar path models attempting to explain behavior as a function of intentions are not consistent with the best-case hypothesis. Consider a logit model

\[ P(y=1|x,i) = \frac{\exp(x\beta + \gamma i)}{1 + \exp(x\beta + \gamma i)} \]

where \((\beta, \gamma)\) are parameters. This model has the property

\[
\begin{align*}
(x\beta + \gamma i) < 0 & \Rightarrow P(y=1|x,i) < 1/2 \\
(x\beta + \gamma i) = 0 & \Rightarrow P(y=1|x,i) = 1/2 \\
(x\beta + \gamma i) > 0 & \Rightarrow P(y=1|x,i) > 1/2.
\end{align*}
\]

Suppose that \(\pi = 1/2\). Then (6) is consistent with (4) only if \((x, \beta, \gamma)\) satisfies the special property \(x\beta \leq 0 \leq x\beta + \gamma\).

The problem is, of course, not specific to the logit model and the case \(\pi = 1/2\). It is characteristic of any path model which attempts to explain \(y\) as a function of a linear index \(x\beta + \gamma i\).

3.3. Prediction Not Conditional on Intentions

Often a researcher wants to predict the behavior of a nonsampled member of the population from which the survey respondents were drawn. Intentions data are available only for the sampled individuals. But some background variables \(x\) may be observed for the entire population. In this setting, one may want to predict behavior conditional on these \(x\). Then the quantity of interest is \(P(y=1|x)\).
The bound (4) implies a bound on $P(y=1|x)$. Observe that

\[ P(y=1|x) = P(y=1|x, i=0)P(i=0|x) + P(y=1|x, i=1)P(i=1|x). \]

It follows from (4) and (7) that

\[ \pi P(i=1|x) \leq P(y=1|x) \leq \pi P(i=0|x) + P(i=1|x). \]

This bound, unlike (4), varies with $x$. The bound width, which is $\pi P(i=0|x) + (1-\pi)P(i=1|x)$, may take any value between zero and one, depending on the magnitudes of $\pi$ and $P(i|x)$. Thus, depending on the application, intentions data may yield a tight or a weak bound on $P(y|x)$. If $\pi = 1/2$, the bound width is 1/2, whatever $P(i|x)$ might be.

The bound (8) is useful in practice if $P(i=1|x)$ can be estimated from the sample data. Under the maintained assumption of random sampling, this is generally possible. If $x$ is discrete, a suitable estimate is the fraction of respondents with observed characteristics $x$ who answer "yes" to the intentions question. If $x$ is continuous, nonparametric regression methods may be applied. See, for example, Prakasa Rao(1983), Manski(1988), or Hardle(1990). Thus (8) provides an estimable bound on $P(y=1|x)$.

It has been known for at least twenty-five years that the sharp relationship

\[ P(i=1|x) = P(y=1|x) \]
need not hold. See Juster (1966), p. 665. Nevertheless, some of the literature continues to consider deviations from this equality as "inconsistencies" in need of explanation. For example, Westoff and Ryder (1977) state:

The question with which we began this work was whether reproductive intentions are useful for prediction. The basic finding was that 40.5 percent intended more, as of the end of 1970, and 34.0 percent had more in the subsequent five years . . . . In other words, acceptance of 1970 intentions at face value would have led to a substantial overshooting of the ultimate outcome. (p. 449)

Seeking to explain the observed "overshooting" of births, the authors state:

one interpretation of our finding would be that the respondents failed to anticipate the extent to which the times would be unpropitious for childbearing, that they made the understandable but frequently invalid assumption that the future would resemble the present— the same kind of forecasting error that demographers have often made. (p. 449)

More recent demographic work maintains the presumption that deviations from (9) require explanation. See, for example, Davidson and Beach (1981) and O'Connell and Rogers (1983).

The best-case hypothesis implies that (9) should hold in one very special case: that in which future behavior depends only on the information available at the time of the survey. In this case, the respondent can forecast his future behavior with certainty. So i always equals y.
In the nondegenerate case where future events partially determine behavior, the best-case hypothesis does not imply (9). Let $1[*]$ denote the indicator function taking the value one if condition [*] is satisfied and zero otherwise. It follows from (2) that

$$P(i=1|x) = \int_{\mathcal{D}_P} p(y=1|s) dP_s | x,$$

provided only that the event $P(y=1|s) = \pi$ occurs with probability zero conditional on $x$. On the other hand,

$$P(y=1|x) = \int_{\mathcal{D}_P} p(y=1|s) dP_s | x.$$

The right-hand sides of (10) and (11) are not generally equal.

A simple example makes the point forcefully. Let $\pi = 1/2$ and let $P(y=1|s) = .51$ for all values of $s$. Then $P(y=1|x) = .51$ but $P(i=1|x) = 1$ for all values of $x$. This demonstrates that individual-level differences between intentions and behavior do not, in general, average-out in the aggregate.
4. CONSISTENT BOUNDS TESTS OF THE BEST-CASE HYPOTHESIS

4.1. The No-Aggregate-Shocks Condition

The probability bounds reported in Section 3 are useful whether or not individuals answering intentions questions actually have rational expectations and make best point predictions of their behavior. If this best-case hypothesis is realistic, then the bounds may be applied in practice. If the best-case hypothesis is not realistic, then intentions data contain less information about behavior than the bounds (4) and (8) claim.

Suppose that one wishes to test the best-case hypothesis in an applied setting where one observes \( x \) and \( i \) on an initial survey of the population and observes \( y \) on a later resurvey. Then one may estimate \( P(i=1|x) \), \( P(y=1|x) \), and \( P(y=1|x,i) \) and check whether the estimates satisfy (4) and (8).

These bounds tests are consistent provided that the estimates for \( P(i=1|x) \), \( P(y=1|x) \), and \( P(y=1|x,i) \) are consistent. Random sampling ensures that the estimate for \( P(i=1|x) \) is consistent. The estimates for \( P(y=1|x) \) and \( P(y=1|x,i) \) are consistent as long as the realizations of the future events \( z \) are not too dependent across the population. This auxiliary condition is sometimes referred to as the absence of "aggregate shocks."

To see the problem that dependence can cause, consider the extreme case in which a single event \( z \) is drawn from the distribution \( P_z|s \), and all the people characterized by \( s \) realize
this event. Then $P(y=1|s)$ continues to be given by equation (1) but, conditioning on $s$, the realized frequency of the event $y = 1$ can be only zero or one, depending on what single realization of $z$ is drawn.

4.2. Empirical Evidence from the NLS72

The NLS72 offers an opportunity to perform the tests. The intentions questions quoted at the beginning of Section 1 were followed by behavior questions asked in the fall of 1974:

What were you doing the first week of October 1971?
(Circle as many as apply)

<table>
<thead>
<tr>
<th>Activity</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Working for pay at a full-time or part-time job</td>
<td>1</td>
</tr>
<tr>
<td>Taking academic courses at a two- or four-year college</td>
<td>2</td>
</tr>
<tr>
<td>Taking vocational or technical courses at any kind of school or college</td>
<td>3</td>
</tr>
<tr>
<td>On active duty in the Armed Forces (or service academy)</td>
<td>4</td>
</tr>
<tr>
<td>Homemaker</td>
<td>5</td>
</tr>
<tr>
<td>Temporary lay-off from work, looking for work, or waiting to report to work</td>
<td>6</td>
</tr>
</tbody>
</table>

These questions about behavior correspond closely, although not perfectly, to the intentions questions asked a year earlier. One difference is that a "temporary lay-off" question was added to the 1974 survey. A second is that the instructions call for respondents to "circle as many as apply" rather than to "circle one number on each line." A third difference is that the respondents to the intentions questions were asked to forecast
their behavior in October 1974, whereas the behavior questions concern the first week of that month. These distinctions will be ignored here, although it is possible that they are germane.

Table 1 presents findings for the case in which \( x \) gives the respondent's sex. The probabilities \( P(i=1|x) \), \( P(y=1|x) \), and \( P(y=1|x,i) \) are estimated by corresponding sample frequencies. For example the estimate of \( P(\text{work}=1|x=\text{male},i=0) \) is based on the 2546 males who said they did not expect to work; the fraction of this group who reported working a year later was .42.

We shall evaluate the findings under the maintained assumption that \( \tau = 1/2 \). Inspection of the table shows that the male and female responses to the "work" and "academic" questions satisfy bounds (4) and (8). So do the male responses to the "military" question and the female responses to the "homemaker" question. The female responses to the "military" question satisfy the bounds except for a modest violation of bound (4) by those stating \( i = 1 \).

On the other hand, the responses of both sexes to the "voc-tech" question and the male responses to the "homemaker" question violate the bounds substantially. Respondents who say they expect to take voc-tech courses subsequently do so only 15 or 16 percent of the time. Males who say they expect to be homemakers later report themselves as such only 9 percent of the time.

It is possible, but unlikely, that these findings reflect sampling variation. The estimates for \( P(i=1|x) \) and \( P(y=1|x) \) are based on samples of roughly 10,000 observations. Those for
P(y=1|x,i) are based on samples whose minimum size is 158 and which typically have several thousand observations. The estimates for P(i=1|x) are from random samples and are extremely precise. The estimates for P(y=1|x) and P(y=1|x,i) are also precise provided only that the no-aggregate-shocks condition holds.

5. FORCED-CHOICE QUESTIONS

A "forced-choice" question requires the respondent to decide what future behavior he would choose if he had to commit himself now. Forced-choice and intentions questions are sometimes confused. Voter election surveys illustrate well the distinction. Some surveys ask:

(*) "For whom do you expect to vote in the coming election, candidate 0 or candidate 1?"

Others ask:

(**) "For whom would you vote if the election were held today, candidate 0 or candidate 1?"

The former is an intentions question, the latter a forced-choice one.

A person need not give the same response to these two questions. The forced-choice response is the person's decision given the information s available at the time of the survey. The intentions response is the person's prediction of the decision he will make when he has the information s and z.
The difference between intentions and forced-choice responses shows clearly if we assume that the person maximizes expected utility. (Until now we have imposed no restrictions on the person's decision rule.) Let $V(s,z)$ denote the difference between the expected utilities the respondent associates with candidates 1 and 0, given the information $(s,z)$. Let $y$ be the candidate for whom the respondent actually votes. Let $i$ be the respondent's response to the intentions question (**). Let $j$ be his response to the forced-choice question (***)

Expected utility maximization implies that

$$(12) \quad y = 1 \Rightarrow V(s,z) \geq 0$$
$$y = 0 \Rightarrow V(s,z) \leq 0.$$

It follows from this and from (2) that

$$(13) \quad i = 1 \Rightarrow P[V(s,z) \geq 0|s] \geq \pi$$
$$i = 0 \Rightarrow P[V(s,z) \geq 0|s] \leq \pi.$$

In the forced-choice setting, the respondent maximizes expected utility conditional on the information $s$ available at the time of the survey. Hence

$$(14) \quad j = 1 \Rightarrow E[V(s,z)|s] \geq 0$$
$$j = 0 \Rightarrow E[V(s,z)|s] \leq 0.$$
Responses i and j clearly need not be the same. For example, suppose that the survey is conducted a week before the election. Suppose that candidate 1 will undergo a medical examination the day following the survey. Let \( z = 1 \) denote the event that the candidate is found healthy and \( z = 0 \) that he has a serious illness. Suppose that a person prefers candidate 1 if the candidate is healthy but prefers candidate 0 otherwise; that is, \( V(s,z=1) > 0 > V(s,z=0) \). Then this person will respond \( i = 1 \) if \( P(z=1|s) > \pi \). He will respond \( j = 1 \) if \( P(z=1|s)V(s,z=1) > P(z=0|s)V(s,z=0) > 0 \).

The difference between (13) and (14) has a particularly simple interpretation if a regularity condition holds. Suppose that the distribution of \( V(s,z) \) conditional on \( s \) is continuous and strictly increasing at the point \( V(s,z) = 0 \). Then (13) is equivalent to

\[
(13)' \quad i = 1 = \text{Q}_{1-\pi}[V(s,z)|s] \geq 0 \quad i = 0 = \text{Q}_{1-\pi}[V(s,z)|s] \leq 0,
\]

where \( \text{Q}_{1-\pi}[V(s,z)|s] \) denotes the \((1-\pi)^{th}\) quantile of \( V(s,z) \) conditional on \( s \). Thus a person will respond differently to intentions and forced-choice questions if, conditioning on \( s \), the \((1-\pi)^{th}\) quantile and expectation of \( V(s,z) \) differ in sign.

The foregoing implies that forced-choice questions should not be used if the objective is to predict future behavior. This does not mean, however, that forced-choice questions are useless.
Suppose that the objective is to learn about the function $V(\ast,\ast)$ and probability distribution $P_i|s$. Then the two types of question have complementary appeal. An intentions question allows one to learn whether $P[V(s,z) > 0|s] > r$. A forced-choice question allows one to learn whether $E[V(s,z)|s] > 0$. Thus the two questions are informative about different properties of $V(\ast,\ast)$ and $P_i|s$.

5. CONCLUSION

The use of intentions data to predict behavior has been controversial. The analysis of this paper suggests that at least some of the controversy is rooted in the flawed premise that divergences between intentions and behavior show individuals to be poor predictors of their futures. Divergences may simply reflect the dependence of behavior on events not yet realized at the time of the survey. Divergences will occur even if responses to intentions questions are the best predictions possible given the available information. The lesson is that researchers should not expect too much from intentions data.

As recognized by Juster (1964, 1966), the yes/no form of intentions question can be improved upon by asking the respondent to give his probability for the behavior in question. Whereas a yes/no question reveals at most the bounds (4) and (8) on $P(y|x,i)$ and $P(y|x)$, probability elicitation may reveal $P(y|s)$. 
In practice, survey researchers do not often elicit probabilities. It is more common to refine yes/no intentions questions by asking for a yes/no/uncertain response, as in the CPS fertility supplement, or for some other multi-category verbal response. The analysis of Section 3 can be extended to find the best-case probability bounds implied by the responses to such questions.
Table 1
Consistency of Schooling-Work Intentions Stated in Fall 1973 with Behavior in October 1974

<table>
<thead>
<tr>
<th>Behavior</th>
<th>Males (4)</th>
<th>Females (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of Observations</td>
<td>Estimate of P(y=1</td>
</tr>
<tr>
<td>Work</td>
<td>7143</td>
<td>.80</td>
</tr>
<tr>
<td>Voc-Tech</td>
<td>1929</td>
<td>.16</td>
</tr>
<tr>
<td>Acad.</td>
<td>1929</td>
<td>.16</td>
</tr>
<tr>
<td>Military</td>
<td>1929</td>
<td>.16</td>
</tr>
<tr>
<td>Homemaker</td>
<td>1929</td>
<td>.16</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Behavior</th>
<th>Males (8)</th>
<th>Females (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimates of P(i=1</td>
<td>x)</td>
</tr>
<tr>
<td>Work</td>
<td>.64 [.32-.82]</td>
<td>.67</td>
</tr>
<tr>
<td>Voc-Tech</td>
<td>.17 [.09-.59]</td>
<td>.05</td>
</tr>
<tr>
<td>Acad.</td>
<td>.43 [.22-.72]</td>
<td>.33</td>
</tr>
<tr>
<td>Military</td>
<td>.09 [.05-.55]</td>
<td>.08</td>
</tr>
<tr>
<td>Homemaker</td>
<td>.02 [.01-.51]</td>
<td>.005</td>
</tr>
</tbody>
</table>

NOTE: The number of observations is not the same across questions because some respondents did not answer some questions. For example, 9689 males (i.e., 7143+2546) answered the work intentions question while 8917 (i.e., 966+7951) answered the military question. The bound (8) is computed for \( \pi = 1/2 \).
References


