Probabilistic Expectations in Developing Countries

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Abstract

Many decisions are made under uncertainty, and individuals are likely to form subjective expectations about the probabilities of events that are relevant to their decisions. I review here a recent and growing literature that uses probabilistic expectations elicited from survey respondents in developing countries. I first present an illustrative model of one particular decision under uncertainty—the choice of a college—to exemplify the importance of subjective expectations data for identification purposes. I then review existing evidence emphasizing that it is feasible to elicit probabilities from survey respondents in low-literacy settings and describe common patterns of answers. Finally, I describe existing applications, many of which seek to assess how expectations influence behavior, in various domains, including health, education, agricultural production, and migration.

1. INTRODUCTION

Many decisions are made under uncertainty, and individuals are likely to form subjective beliefs (expectations) about the probabilities of events that are relevant to their decisions. Preferences and expectations are then combined, potentially within a subjective expected utility framework, to reach a choice. Typically, researchers observe only the final outcomes and have data on choices. This leaves them with a basic identification problem when making inferences on the decision-making process as many combinations of preferences and expectations can lead to the same observed choice (Manski 2004). For example, the lack of investment in education in many developing countries could result from systematic misperceptions about the returns to schooling, limited taste for acquiring education, or both (along with other explanations, such as credit constraints or lack of access to schools). One possibility to mitigate this identification problem is to ask decision makers directly about their subjective expectations. Data on subjective expectations and choices can then be combined to make inferences on preferences (Delavande 2008). Data on subjective expectations are also by themselves important to identify potential misperceptions in the population about important life events.

In surveys, researchers commonly ask respondents about verbal expectations (e.g., is this event "very likely" or "very unlikely"?), but those questions yield only ordinal measures of beliefs. Moreover, responses may not be interpersonally comparable. These concerns lead to the elicitation of probabilistic expectations, for which respondents are asked a question that can be interpreted as a probability. Such quantities are helpful to assess whether individuals have accurate expectations about the future and can be used in economic models that require quantitative measures of probabilities and uncertainty. I refer the interested reader to Manski (2004) and Hurd (2009), who review the literature on the elicitation of expectations in developed countries. Important findings include that people are able and willing to provide their expectations in a probabilistic format, there is substantial heterogeneity in beliefs (underscoring the importance of collecting expectations data rather than making assumptions about expectations), and expectations tend to vary with observable characteristics in the same way as actual outcomes [e.g., smokers report lower subjective probability of survival than do nonsmokers (Hurd & McGarry 1995)].

My focus here is on developing countries. Obtaining probabilistic expectations data in developing countries is particularly relevant because individuals face a host of sources of uncertainty, and understanding their decision-making process is crucial for the design of effective policy. However, these data may at first appear challenging to collect owing to the low literacy of individuals in many settings. Delavande et al. (2011b) review the literature measuring expectations in developing countries and reach conclusions similar to the studies based in developed countries: Survey respondents can generally understand and answer probabilistic questions, such questions are not prohibitively time-consuming to ask, and the expectations are useful predictors of future behavior and economic decisions. Attanasio (2009) discusses some specific issues in their measurement, validation, and use.

In the present review, I start in Section 2 by providing an illustrative model of college choice in urban Pakistan, taken from Delavande & Zafar (2013), to exemplify the role of subjective expectations in how individuals make decisions under uncertainty and the importance of having expectations data for identification purposes. I then review in Section 3 how expectations have been measured so far, the typical patterns of answers, and the validation exercises that have been undertaken. In Section 4, I focus on the substantive aspects and report findings from studies (most of them very recent and many still unpublished) in which subjective expectations have been elicited and used in a developing-country context in four important domains: health, education, input and output in agricultural production, and income and wealth. At a time at which randomized interventions are rolled out all over the world, I also report on a recent attempt to elicit expectations about the impact of interventions from academics, policy makers, and experts. I conclude in Section 5.

2. USING EXPECTATIONS DATA TO BETTER UNDERSTAND DECISION MAKING UNDER UNCERTAINTY: AN ILLUSTRATIVE MODEL OF COLLEGE CHOICE IN PAKISTAN

In this section, I present a model of college choice in Pakistan to illustrate the advantage of having probabilistic expectations to better understand how individuals make decisions under uncertainty. The model is a slightly modified version of the model from Delavande & Zafar (2013), where we analyze the decision process of male Pakistani students. In the Pakistani context, students seeking to attend university can choose between a wide array of institutions, which vary in terms of their type of teaching, tuition fees, and returns. Delavande & Zafar (2013) focus on three distinct school types belonging to different parts of the higher-education spectrum in Pakistan. At one end are Western-style universities that are similar to American colleges: They provide a liberal arts curriculum, are expensive, and are associated with high–labor market returns. At the other end are Madrassas, Islamic religious seminaries, which focus on religious teaching without any secular or vocational training. Madrassas generally tend to be free, and their labor market returns tend to be low. Finally, the third school type, Islamic universities, lies somewhere in the middle: These universities provide a liberal arts curriculum combined with Islamic teachings and courses and tend to charge tuition in the low to middle range.

A student lives for $T+1$ periods. In period $t=0$, the first period of his life, student i acquires (higher) education. At the beginning of the period, the student chooses a school s where he enrolls. At the end of the period, the student leaves school by either graduating or exogenously dropping out and enters the labor market where he stays in period $t=1,\ldots,T$. In our setup, the student's most important decision is the choice of school. The choice is important not only because it affects the stream of future earnings (and thus consumption), but also because of the two following individual and school-specific factors that the student values directly: a^1_{is}, whether the school's teachings are consistent with student i's ideology, and a^2_{is}, whether the student's parents approve of the school. In addition, the student cares about the location l_{is} of the school (i.e., whether the school is located in the same or a different city than family residence). For tractability, we assume that the utility function is additively separable, linear in the school outcomes and location, and logarithmic in consumption. Thus, we have that the utility of individual i from attending school s is given by

$$U_{is} = \sum\nolimits_{j=1}^{2} \alpha_j a^j_{is} + \delta l_{is} + \theta \sum\nolimits_{t=0}^{T} \beta^t \ln(c_t) + \gamma_s + \varepsilon_{is},$$

where α_j is the utility value of outcome a^j_{is}, δ is the utility value of the school's location, β is the rate of time preference, c_t is student i's consumption at time t, θ is the utility value of log consumption, γ_s is a school-specific constant, and ε_{is} is a random term that is individual and school-specific and unobservable to the econometrician. Consistent with the lack of well-functioning credit markets in Pakistan, there is no borrowing or lending possible, so student i will consume his earnings at every period from $t=1$ to T. Let y_{ist} denote student i's time t earning if he has enrolled in school s. At time $t=0$, student i needs to finance schooling out of his parent's earnings y_{i0} and faces (perceived) cost

C_{is} if he enrolls in school s. The per period budget constraints (conditional on entering school s) are therefore given by

$$c_0 + C_{is} \leq y_{i0},$$
$$c_t = y_{ist} \text{ for } t = 1 \text{ to } T.$$

Because the student cannot borrow to finance the school cost, student i solves his maximization problem by restricting the choice set to schools for which the period-zero budget constraint $c_0 + C_{is} \leq y_{i0}$ is not violated, that is, schools for which the costs do not exceed parents' income. Let S_i denote the set of schools s that satisfy student i's period-zero budget constraint.

A key feature of the model is that, at $t = 0$, the student faces uncertainty about the school-specific outcomes as well as lifetime earnings associated with each choice. For example, the student may be unsure about the type of teaching taking place in a school and the future labor market earnings if he were to graduate from a particular school. Student i possesses beliefs about the distribution of these events, conditional on each school s. We denote this distribution by $G_{is}\left(\{a^j\}_{j=1}^2, \{y_t\}_{t=1}^T\right)$. The distributions of future events $G_{is}\left(\{a^j\}_{j=1}^2, \{y_t\}_{t=1}^T\right)$ represent unresolvable uncertainty as these events will not have occurred at the time of school choice. Student i chooses the school among his feasible choice set that maximizes subjective expected utility subject to his budget constraints; that is, the student solves

$$\max_{s \in S_i} \int \left\{ \begin{array}{c} \sum_{j=1}^2 \alpha_j a^j + \delta l_{is} + \theta \ln(y_{i0} - C_{is}) \\ + \theta \sum_{t=1}^T \beta^t \ln(y_t) + \gamma_s + \varepsilon_{is} \end{array} \right\} dG_{is}\left(\{a^j\}_{j=1}^2, \{y_t\}_{t=1}^T\right). \tag{1}$$

Because of the separability assumption of the utility, only marginal beliefs matter to solve this maximization problem. We denote by $P_{is}(a^j)$ the marginal probability about the factors a_{is}^j. Regarding future earnings, student i is uncertain about (a) whether he would successfully graduate or drop out if he enrolls in school s, (b) whether he would find a job in each of these cases, and (c) what his earnings would be for each of these scenarios. Student i therefore possesses the following school-specific subjective probabilities: the probability $P_{is}(d)$ of dropping out from school s if he enrolls in s, the probability $P_{is}(\text{job} \mid d)$ of finding a job if he drops out after enrolling in school s, and the probability $P_{is}(\text{job} \mid g)$ of finding a job if he graduates from school s after enrolling in s. The student also possesses subjective expectations Y_{isht} about labor earnings at time t if he enrolls in school s and either drops out ($h = d$) or graduates ($h = g$). We assume for simplicity that $P_{is}(\text{job} \mid d)$ and $P_{is}(\text{job} \mid g)$ are time invariant. Because unemployment benefits do not exist in Pakistan, we normalize earnings to 1 if a student is not employed. Under those assumptions, Equation 1 can be written as

$$\begin{aligned} \max_{s \in S_i} \Big\{ & \sum_{j=1}^2 \alpha_j P_{is}(a^j) + \delta l_{is} + \theta \ln(y_{i0} - C_{is}) \\ & + \theta \sum_{t=1}^T \beta^t \left[P_{is}(d) P_{is}(\text{job} \mid d) \ln(Y_{isdt}) + (1 - P_{is}(d)) P_{is}(\text{job} \mid g) \ln(Y_{isgt}) \right] \\ & + \gamma_s + \varepsilon_{is} \Big\}. \end{aligned} \tag{2}$$

The goal is to infer the parameters of the utility function and measure the relative role of future earnings and nonpecuniary outcomes on the decision to attend a given college.

Economists have long been interested in knowing whether expectations about future earnings (or about returns to schooling) influence school or occupational choice. Without data on expectations, the prior literature makes various types of assumptions for the mapping between realized earnings and expected earnings. For example, Willis & Rosen (1979), Berger (1988), Flyer (1997), Arcidiacono (2004), and Beffy et al. (2012) evaluate the role of earnings expectations on college attendance, college major, or choice of occupation. They rely on earnings data and the rational expectations assumption to predict individuals' earnings expectations. This approach overlooks that subjective expectations may be rather distinct from realized earnings and assumes that the formation of expectations is homogeneous (sometimes only within a group sharing certain characteristics, such as ability or gender). Making inference on the decision-making process based on choice data and those maintained assumptions on expectations is problematic because, as pointed out in Section 1, observed choices might be consistent with several combinations of expectations and preferences (see also discussion in Manski 1993).

An alternative approach is to collect subjective expectations data from survey respondents, to avoid making noncredible assumptions on expectations. The survey undertaken by Delavande & Zafar (2013) contains data on all the subjective probabilities relevant in the model described above.[1] Their paper discusses additional assumptions required for identification of the utility parameters.

3. MEASURING PROBABILISTIC EXPECTATIONS IN DEVELOPING COUNTRIES

3.1. Design

I now discuss the various designs that have been used to elicit probabilistic expectations from survey respondents in developed countries.

3.1.1. Using percent chance in more literate contexts. In developed-country surveys, the standard method of eliciting subjective probabilities is to ask people these probabilities using a percent chance format (see Manski 2004 and Hurd 2009 for reviews of the literature). For example, the US Health and Retirement Study asks respondents the following question: "What is the percent chance that you will live to be 75 or more?"

Similar question wording has been used in developing countries in a context where respondents are literate. Examples of the use of this same percent chance formulation are by McKenzie et al. (2013), who ask Tongans their expectations of income if they were to migrate to New Zealand; Delavande & Zafar (2013), who ask college students in Pakistan a series of expectations questions, including the percent chance of graduating from college, the chance of being employed, and the chance of earning above certain thresholds; and Attanasio & Kaufmann (2012a,b), who elicit employment and income expectations of high school students in Mexico.

3.1.2. Using visual aids and physical objects. The above studies have shown that in some settings, the percent chance format used in developed countries has been successfully employed in developing countries. However, in many settings in which respondents are less literate, researchers feel that simply asking respondents for a percent chance is too abstract, and visual aids are needed to help them express probabilistic concepts. This commonly involves asking respondents to allocate stones, marbles, or beans. In the Malawi Longitudinal Study of Families and Health (MLSFH; formerly the Malawi Diffusion and Ideational Change Project), Delavande & Kohler

[1] Respondents were asked only about age-30 earnings rather than earnings at every age (see assumptions on earnings growth made in Delavande & Zafar 2013).

(2009) ask respondents to choose 10 beans to express the likelihood of an event happening. Their instructions to the respondents read as follows:

> I will ask you several questions about the chance or likelihood that certain events are going to happen. There are 10 beans in the cup. I would like you to choose some beans out of these 10 beans and put them on the plate to express what you think the likelihood or chance is of a specific event happening. One bean represents one chance out of 10. If you do not put any beans in the plate, it means you are sure that the event will NOT happen. As you add beans, it means that you think the likelihood that the event happens increases. For example, if you put one or two beans, it means you think the event is not likely to happen but it is still possible. If you pick 5 beans, it means that it is just as likely it happens as it does not happen (fifty-fifty). If you pick 6 beans, it means the event is slightly more likely to happen than not to happen. If you put 10 beans in the plate, it means you are sure the event will happen. There is not a right or wrong answer, I just want to know what you think. Let me give you an example. Imagine that we are playing Bawo. Say, when asked about the chance that you will win, you put 7 beans in the plate. This means that you believe you would win 7 out of 10 games on average if we play for a long time.

The use of 10 or 20 physical objects with a design as above is now quite standard and often used in the applications I review below. In some studies, respondents are asked to think of people like themselves (sometimes in combination with physical objects) and to report how many would experience the event. For example, de Mel et al. (2008) ask respondents to think "about 20 businesses that are JUST LIKE YOURS. The owners have the same age, education, experience, skill level, commitment and similar locations to you," whereas Aguila et al. (2013) ask respondents to consider "people like you."

This wording may be appealing, but one needs to keep in mind that the obtained answers may vary slightly from those asking about the respondents directly, as respondents may make various assumptions about the nonspecified characteristics of those hypothetical individuals. A subsample of respondents from the Longitudinal Aging Study in India (LASI) was asked expectations questions about their mortality over 1 year, 5 years, and 10 years. For all time horizons, respondents were asked two different questions: (*a*) "Pick the number of beans out of 10 that reflects how likely you think it is that you will die within a one-year period beginning today," and (*b*) "think about 10 people like you (same age, gender, income, etc . . . .). Pick the number of beans that reflects how many will be dead in one year." **Figure 1** presents the difference between one's own mortality expectations within 1 year and those of the hypothetical individuals.[2] It shows that a large proportion (63%) of the respondents provide different answers to the two questions, and that 41% report a difference equal to or greater than two beans (i.e., 20 percentage points). One advantage of the hypothetical scenario is that, in this particular context about mortality, item nonresponse is lower compared to the wording asking about one's own mortality (9% versus 12%). There is therefore a potential trade-off between asking about the respondents themselves and about people like themselves.

When respondents are asked about a binary event (e.g., being HIV positive), they simply allocate the number of beans for this event. When respondents are asked about the distribution of a continuous outcome (e.g., income), respondents are requested either to report multiple points in

[2]Half the respondents were asked about mortality, while the other half were asked about survival. **Figure 1** pools all answers after having rescaled the survival ones as mortality. Whether respondents were asked about survival or mortality does not affect how one's own mortality expectations and those of hypothetical individuals differ.

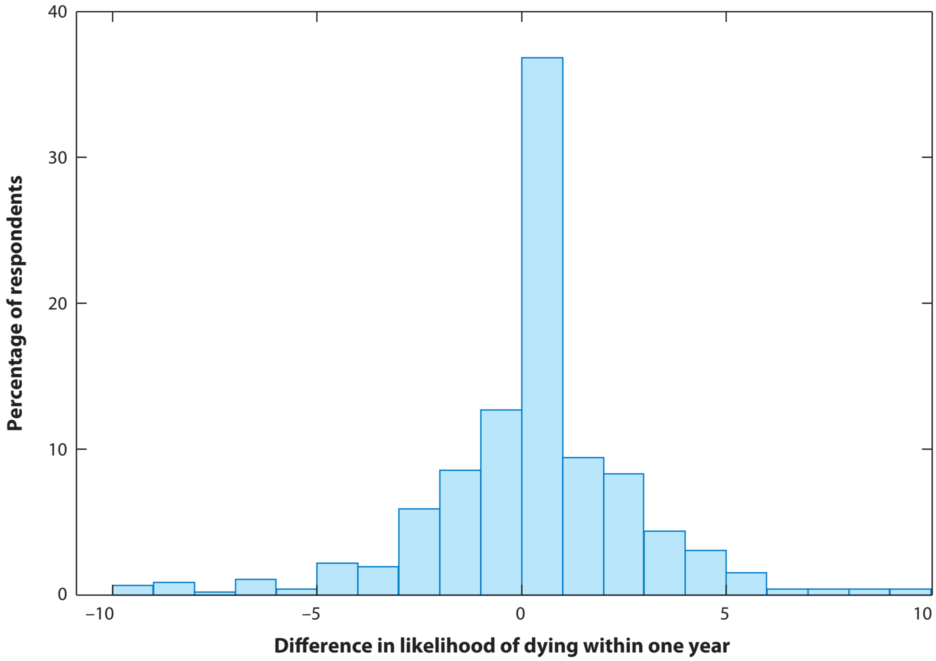

Figure 1

Histogram of the difference in the likelihoods of dying within 1 year (own minus hypothetical individual) from the Longitudinal Aging Study in India (456 observations).

their cumulative distribution function [e.g., Delavande & Kohler (2009) ask respondents to report the likelihood of dying within 1 year, 5 years, and 10 years] or to allocate the beans into several intervals to provide information on the density function. When eliciting a distribution using the latter manner, an important design issue is how to specify a set of intervals for respondents to allocate these items to, and how to define the support over which expectations are elicited. One method is to use a common, predetermined support for all respondents. Pre-existing data or prior knowledge of the range of possible values of the outcome is used to define the support, and a relatively large number of intervals is often given within this support. Another method is to first ask individuals their perceived maximum and minimum for the outcome being studied and then use these to define a relatively small number of self-anchored intervals within this range (see discussion in Delavande et al. 2011b). A relevant question in this context is how to interpret the minimum and the maximum. Dominitz & Manski (1997) find that reported minimum and maximum future incomes actually corresponded to nonextreme subjective probabilities when probabilities were elicited as points on a cumulated distribution function. On average, the minimums were at the 20% level and the maximums at the 80% level. Delavande et al. (2011b) report that, in the data from McKenzie et al. (2013) in which individuals in Tonga are asked about income expectations, maximums tend to correspond to the 95th or 90th percentile of the subjective distribution. One may therefore need to widen the range beyond the reported minimum and maximum when defining the support to be used to elicit expectations.

Delavande et al. (2011a) carry out a methodological randomized experiment with boat owners in India to test the sensitivity of expectations about future fish catches to several variations in elicitation design, including that respondents were asked about the distribution of the value of future catches using both a predetermined support with many intervals and a self-anchored support with only four intervals, with the order of these questions randomized. The self-anchored method requires the elicitation of the maximum and minimum of the support, and several midpoints are computed in between (as in Giné & Klonner 2007, Attanasio & Kaufmann 2012a,b). The advantage of the self-anchored support is that it asks respondents about the range of values that are relevant to them. The disadvantage, however, is that it requires real-time calculations by the interviewer, which can be time-consuming and subject to interviewer calculation error, so in practice, the feasible number of intervals is limited. In contrast, a predetermined support can accommodate more intervals, but if the support is very heterogeneous across respondents, then intervals will be wide to encompass everyone's relevant range. Reassuringly, the results show that the distributions elicited with a predetermined support and many intervals are remarkably consistent with the self-anchored distribution with a small number of intervals. However, in this context, the most accurate distributions are obtained using 20 beans (rather than 10) and a predetermined support.[3]

3.2. Patterns of Answers

An initial concern in the elicitation of probabilistic expectations (in both developed and developing countries) was that it may not be possible to gather probabilistic answers because many individuals (especially illiterate ones) do not understand the concept of probability. I briefly review here evidence that shows that elicited probabilistic expectations appear to be coherent and meaningful according to the following set of criteria: (*a*) Item nonresponse rates are typically very low, (*b*) respondents' answers follow basic properties of probabilities, (*c*) expectations vary with respondents' characteristics in the same way as actual outcomes vary with those characteristics, and (*d*) they are correlated with past and future outcomes in the expected direction (additional details and discussion can be found in Delavande et al. 2011b). Another common theme of existing studies is the vast heterogeneity in elicited expectations.

3.2.1. High response rate. Item nonresponse rates on the expectations questions tend to be quite low based on the evidence from studies that report them, with less than 2% in the MLSFH (Delavande & Kohler 2009) and less than 4% in several household studies in Bangladesh and India asking about health- or income-related events (Tarozzi et al. 2009, Mahajan et al. 2011, Attanasio & Augsburg 2012). In LASI, item nonresponse rates tend to be higher but are still relatively low (between 2% and 12%, with higher item nonresponse on the mortality question).

3.2.2. Respect of basic properties of probabilities. Delavande & Kohler (2009) investigate whether respondents in rural Malawi understand the concept of probability by asking about two nested events: going to the market within (*a*) two days and (*b*) two weeks. If respondents understand the concept of probability, they should provide an answer for the two-week period that is larger than or equal to the one for the two-day period. A remarkably high number of respondents provided an answer for the event "going to the market within two days" that was smaller than or equal to their answer for the event "going to the market within two weeks." Only 0.6% violated the property of the probability of nested events. This high consistency rate is not driven by respondents providing the same answers to both questions (only 6% of the respondents did).

[3]Respondents were asked about the value of fish expected to catch in a day in the month of August, which can then be compared with the realized distribution of daily catches during that month at the individual level to assess accuracy. This is a unique feature of this setting, as, in many other cases, one observes only one realization at the individual level.

Tarozzi et al. (2009) and Delavande et al. (2011a) use a similar framework with nested events, and both studies report that none of their respondents violated the monotonicity property. Among older Indian respondents, these types of questions seem more challenging for some: In LASI, 24% violated the monotonicity property. Delavande et al. (2011a) also ask another basic numeracy question: "Imagine I have 5 fishes, one of which is red and four of which are blue. If you pick one of these fishes without looking, how likely is it that you will pick the red fish?" Of the respondents, 99% provided the correct answers. Also reassuringly, all respondents answered zero when asked about a zero-probability event (the likelihood of not catching any fish in the month of August if one goes fishing 6 days a week) and answered one when asked about a certain event (the likelihood of eating fish at least once during the month of August). Overall, the results from these studies suggest that a vast majority of respondents in developing countries understand the concept of probabilities.

3.2.3. Expectations and respondents' characteristics. The few papers that have looked at the relationship between expectations and respondents' characteristics show that expectations vary with characteristics in the same way, at least qualitatively, as actual outcomes vary with those characteristics. Delavande & Kohler (2009) find that, despite substantial heterogeneity in beliefs, the mean and percentiles of the distribution of beliefs vary with observable characteristics in the a priori expected direction. For example, respondents' subjective probabilities about experiencing food shortages in the next 12 months vary meaningfully with respondents' socioeconomic status, such as education, land ownership, and level of savings. Similarly, mortality expectations vary with age, time horizon, education, HIV status (not known to the respondents at the time of the survey), and number of sexual partners, as expected. Similarly reassuring associations are found regarding income expectations (e.g., Attanasio et al. 2005, Attanasio & Augsburg 2012, McKenzie et al. 2013). For example, Attanasio & Augsburg (2012) find that in the Indian context, households headed by someone with formal education, married individuals, or individuals belonging to a higher caste expect a higher income in the coming year. Attanasio et al. (2005) find that in the Colombian context, more educated individuals expect a higher income in the coming month.

3.2.4. Expectations and past outcomes. Several studies document that past outcomes experienced by individuals are correlated with expectations about future outcomes. In Malawi, respondents who have used condoms in the past are more likely to expect to use condoms in the future (Delavande & Kohler 2009). In Uganda, the most recent coffee price received by a farmer is negatively associated with the subjective probability of a negative return to coffee production (Hill 2010).

Some studies also compare expectations to historical realizations. In a stationary environment, this can be useful to assess the accuracy of beliefs. In Malawi, the ordering of the mean and percentiles by region of the distribution of answers regarding experiencing food shortage is consistent with historical regional variation in drought and food shortage, and the patterns of answers of beliefs about infant mortality match those of actual regional variations (Delavande & Kohler 2009). In India, the lower and upper bounds of both the subjective and historical distributions of the period for the onset of the monsoon season are remarkably similar (Giné et al. 2009).

3.2.5. Heterogeneity in beliefs. Despite the regularity in the data highlighted above (i.e., that expectations vary with characteristics and past outcomes as expected), it is important to point out the substantial heterogeneity in beliefs, irrespective of the events considered. I illustrate this claim in **Figure 2**, which shows the distribution by education of the subjective likelihood that

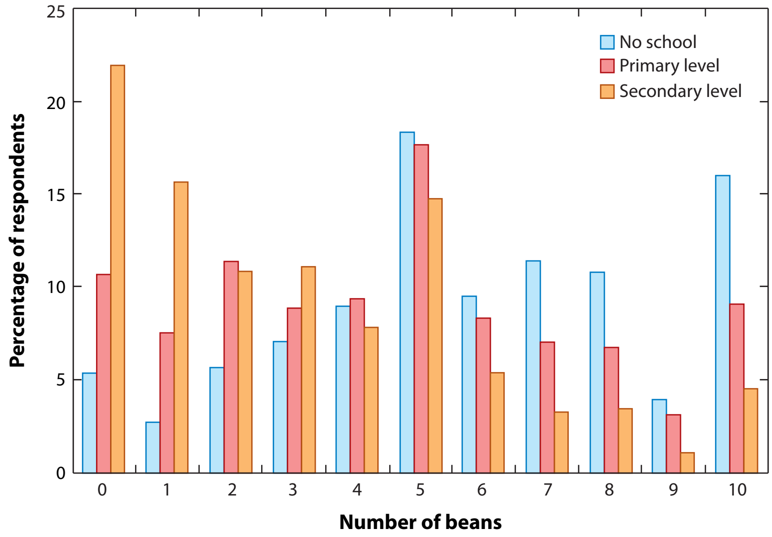

Figure 2

Distribution by education of the likelihood (from zero to 10 beans) that respondent will experience a food shortage in the next 12 months from the 2006 Malawi Longitudinal Study of Families and Health, in percentage of respondents (3,201 observations).

a respondent will experience a food shortage in the next 12 months from the 2006 MLSFH. The figure clearly shows a gradient by education, with less-educated respondents being more likely to believe that they will experience a food shortage in the next 12 months, as mentioned in Section 3.2.3. For example, among respondents with no schooling, 16% allocated 10 beans for the event, compared to 9% and 5% among those with primary and secondary education, respectively. But **Figure 2** similarly emphasizes the heterogeneity in beliefs, even within an education category. For example, among the respondents with secondary education, 22% allocated zero beans, 15% allocated 5 beans, and 5% allocated 10 beans.

4. RECENT APPLICATIONS: EXPECTATIONS, INFORMATION, AND DECISION MAKING UNDER UNCERTAINTY IN DEVELOPING COUNTRIES

4.1. Health

Subjective expectations are important determinants of health-related behaviors in developing-country contexts as individuals face substantial uncertainty about their own and other family members' health, the relationships between health inputs and health outcomes, the effectiveness of treatment strategies and health-seeking behaviors, and the risk environment affecting the severity of the disease burden and the consequences of behavioral choices. Health interventions providing treatments for diseases, or guidance for risk-reducing behaviors, may also fail or be inefficient if the perceived effectiveness deviates from the actual effectiveness of treatments/behavioral changes. Without direct evidence on health-related expectations, the decision processes affecting an individual's health in developing countries can only be poorly understood, thereby also limiting the ability to devise effective health interventions. Despite this centrality of subjective expectations for health decision making in developing countries, little is known about health-related subjective expectations in these contexts. I review available evidence here, with some work focusing on how beliefs influence health-related decision making and other work looking at how new technology or information changes health-related beliefs.

Because of the richness of the expectations data of the MLSFH and the policy relevance of the topic, a set of papers focuses on HIV/AIDS-related issues in rural Malawi. In particular, Delavande & Kohler (2013) and de Paula et al. (2014) investigate the causal impact of HIV/AIDS-related beliefs (including beliefs about one's own HIV status) on the decision to engage in risky sex. One concern particularly relevant to their application is the potential endogeneity of beliefs arising from the dependence of current beliefs on past behaviors. Unobserved heterogeneity capturing time-invariant preferences for risky sex may be correlated with beliefs about one's own HIV status if, for example, individuals revise their beliefs about the chance of being infected with HIV upward after engaging in risky sex, or if this unobserved heterogeneity also influences the decision to get tested for HIV. De Paula et al. (2014) evaluate the role of beliefs about one's own HIV status on men's likelihood of having extramarital sex or multiple sexual partners. They use a panel data estimator that accommodates unobserved heterogeneity as well as belief endogeneity arising from the dependence of current beliefs on lagged behaviors. They find that downward revisions in the subjective probability of being HIV-positive increase risky behavior, whereas upward revisions decrease it.

Delavande & Kohler (2013) investigate the role of HIV/AIDS-related expectations on the decision to have multiple sexual partners. They develop a two-period model that highlights the role of expectations in the decision to engage in risky sexual behavior. The framework shows that the difference in subjective survival probability associated with having risky sex versus having safe sex is crucial for decision making. It also shows that this difference in probability depends in turn on a set of six subjective expectations: (*a*) expectations of survival conditional on being healthy, (*b*) expectations of survival conditional on being infected, (*c*) expectations about one's own HIV status, (*d*) expectations about partners' HIV status, (*e*) expectations about the HIV transmission rate associated with safe sex, and (*f*) expectations about the HIV transmission rate associated with risky sex. Distinctively, the MLSFH has data on all those expectations that are potentially relevant to behavior. Delavande & Kohler find that the difference in subjective survival probability associated with having multiple sexual partners versus having one partner plays an important role in determining the decision to have multiple sexual partners. They also simulate the impact of various policies that would influence individual expectations. They find that a (hypothetical) information campaign on HIV transmission risks, leading people to revise their subjective beliefs about transmission risk to available statistics from medical studies, would have a perverse effect and increase the probability of having multiple partners. This is because respondents widely overestimate the relative impact of having multiple partners on the average probability of becoming infected with HIV compared to having one partner. However, providing information on the mortality risk of someone healthy and that of someone infected with AIDS, leading people to revise their beliefs to available statistics from life tables, would have a positive impact. This is because individuals underestimate the magnitude of the negative impact of HIV/AIDS on survival.

Shapira (2013) also uses data from the MLSFH to investigate the role of subjective beliefs about HIV status on fertility decisions. He develops a dynamic discrete-choice life-cycle fertility model in which expectations about the life horizon and child survival depend on a perceived infection hazard. The estimated structural model is used to conduct counterfactual simulations. The presence of HIV is found to reduce the average number of births a woman has during her life cycle. The paper also finds that HIV testing can reduce the fertility of infected women, whereas the prevention of mother-to-child transmission has limited impact on fertility.

Delavande & Kohler (2012) investigate the causal impact of learning one's own (and potentially spouse's) HIV status on beliefs about HIV status and transmission risk (and sexual behavior). The HIV testing procedure was part of a randomized experiment to study the determinants of HIV testing uptake (Thornton 2008), which allows the authors to implement instrumental variables techniques to control for the potential selection associated with respondents choosing to learn their HIV status. The authors find that receiving an HIV-negative test result implies (*a*) higher subsequent subjective probabilities about being infected with HIV, although the effect is small in magnitude, and (*b*) larger prediction errors about one's own HIV status. However, the effect disappears among individuals in HIV-negative couples who also learned the status of their spouse. The authors also find that learning an HIV-positive status has no effect on the reported probability of being infected in the medium run but decreases the subjective probabilities about transmission rates associated with various behaviors. The latter results may be driven by the fact that some respondents who tested positive found out that their main partner was HIV-negative.

Baranov & Kohler (2013) and Baranov et al. (2012) focus on the introduction of a new technology on beliefs (and outcomes). They investigate the impact of the rollout of antiretroviral therapy (ART) in Malawi on the subjective probability of survival, savings, human capital investment, agricultural labor supply output, and mental health. They use a difference-in-difference identification strategy and find that ART availability substantially reduces subjective mortality risk, including among HIV-negative respondents. They also find that ART has a large and significant impact on savings and human capital investment, measured by expenditures for schooling and children's medical expenses. These effects seem to be driven by the improvement in perceptions of life expectancy.

Another set of papers looks at beliefs about the health consequences of available technologies (or health behavior) and their role in determining health-seeking decision making. Mahajan et al. (2011) and Mahajan & Tarozzi (2012) seek to understand the low take-up rate of bed nets in malaria-prone regions in India despite the fact that insecticide-treated nets (ITNs) provide effective protection against malaria, particularly among pregnant women and children. Cost is often cited as a barrier to take-up, along with misperceptions about malaria and the effectiveness of bed nets. In these two papers, the authors ask respondents to report their probabilistic beliefs about the likelihood that an adult, a child under 6, and a pregnant women contract malaria in the next year under three different scenarios: The individual makes regular use of an ITN, an untreated net, or no net at all. The expectations data reveal three main findings: (*a*) Untreated nets are perceived as effective against malaria, and ITN even more so; (*b*) there are few differences in beliefs according to whether the individual in the scenarios was a child, a pregnant woman, or an adult, despite the fact that adults, who have developed partial immunity, are less likely to develop symptoms; and (*c*) beliefs are strongly concentrated at the focal answers of zero for the ITN scenarios, 5 for the untreated net scenarios, and 10 for the no-net scenarios, although there is still heterogeneity in beliefs.[4] They also ask respondents beliefs about village-level ownership of ITNs.

Mahajan et al. (2011) use net ownership data collected at the same time of the expectations data to study the determinants of net ownership. They discuss identification with both nonparametric and parametric utility as well as parametric and semiparametric specification for the unobserved heterogeneity. Variation in beliefs is one key requirement for identification. They used their estimated structural parameters to evaluate how a change in beliefs about the effectiveness of ITNs

[4]Heaping at focal answers is common in developed countries but is less so in developing countries where physical objects are used. In the baseline survey of Mahajan et al. (2011), respondents were asked to report their probabilistic beliefs using their fingers rather than loose physical objects, which may have led respondents to be more likely to report zero, 5, or 10. At the follow-up, in which marbles were used, heaping is much less frequent.

or price would influence net ownership and conclude that changing either would have a very limited impact. Increasing the beliefs about village-level ownership of ITNs has a larger effect on take-up.

Mahajan & Tarozzi (2012) also make use of the expectations data to identify utility parameters, with a major focus on time preference parameters (and allowing for hyperbolic preferences) in the context of the decision to purchase bed nets on credit and retreat them 6 months and 12 months after purchase. Nonstandard preferences displaying biases toward the future have been put forward as an explanation for why poor individuals in developing countries make seemingly inefficient choices. The identification of heterogeneous time preference parameters is achieved by the availability of expectations data, responses to time preference questions, and a field experiment in which different contracts, designed to appeal differently to individuals with different degrees of sophistication in their time inconsistency, were offered to survey respondents (the purchase of bed nets on credit or the purchase of bed nets and future net retreatment on credit). The authors estimate that time-inconsistent agents account for more than half the population. Yet most of those time-inconsistent agents have preferences very similar to time-consistent agents, suggesting that time-consistent behavior may be a reasonable approximation of the bulk of the population.

Tarozzi et al. (2009) seek to understand households' choice of the source of drinking water in Bangladesh, where arsenic-contaminated water is a serious public health problem. They assess respondents' perceptions of the health consequence from drinking contaminated water by asking the likelihood of either a child or an adult developing skin lesions or experiencing serious health problems if they drink water from an unsafe well for a month and then 1, 10, or 20 years. The unsafe well is described as having an arsenic level just above what the government says makes a well unsafe. The data reveal three important facts. There is widespread awareness that (*a*) arsenic may lead to skin lesions, (*b*) longer exposure to unsafe water is more detrimental to one's health, and (*c*) children are more vulnerable than adults to arsenic exposure. Yet there is still considerable variation in beliefs. Respondents were then provided with the arsenic level of their source of drinking water and randomized into two different health-risk communication strategies about the danger of contaminated water, and follow-up beliefs were elicited. Surprisingly, follow-up beliefs revealed a shift toward more concerns for the detrimental health effect of short-term exposure and less concerns for long-term exposure. Respondents were also asked the health consequences from drinking from their own well. After having learned the arsenic level, respondents' beliefs reveal a higher perceived health risk from drinking from the tested well when its arsenic content is unsafe. Tarozzi et al. (2009) then evaluated whether the choice to switch to a different source of drinking water is predicted by the risk perception and find that, conditional on the actual arsenic level, a higher probability of health risk with the tested well increases the probability of switching to a different water source, although the effect is small in magnitude.

4.2. Education

A recurrent theme in developing countries is that the stock of education is low and differs by gender, despite the fact that returns to education tend to be high. There are several explanations for this, including credit constraints, lack of access to schools for many, or high discount rates. Another important channel may be that parents and youth are misinformed about the returns to schooling, leading them to make suboptimal school choice. Several recent papers examine the role of subjective expectations about monetary (and sometimes nonmonetary) returns to schooling on the decision to go to school.

In a series of papers, Kaufmann (2012) and Attanasio & Kaufmann (2012a,b) analyze new expectations data elicited from youth in Mexico (or their mothers if the youth were absent) about the age-25 probability of working and the subjective distribution of age-25 income conditional on various highest educational attainments. In particular, respondents were asked to state their minimum and maximum earnings conditional on working and the probability that the earnings would be above the average of the minimum and maximum. The highest educational attainment considered depends on the age of the youth and can be of three kinds: junior high school completion, senior high school completion, and college completion. The data reveal that youth expect higher earnings and lower labor market risk (namely earnings and unemployment risk) with higher educational attainment.

Attanasio & Kaufmann (2012b) examine the role of expectations about returns to schooling and of perceptions of labor market risks in the decision to continue further education. They use a reduced-form approach in which the dependent variable is an indicator for whether the student enrolls in college or junior high school, and the independent variables of interest are (*a*) the monetary returns of going to college (as defined by the difference in age-25 expected log earnings between college and senior high school completion), (*b*) the variance of the log of earnings, and (*c*) the subjective probability of age-25 employment under the different educational attainment scenarios.[5] In a sample of senior high school graduates, the authors find that expectations about future income are a significant predictor for the decision to enroll in college for boys but not for girls. They also find that mothers' expectations about employment are significant predictors in the decision to enroll in college for girls but not boys. This suggests that mothers take an important part in their daughters' decisions to attend college but not their sons'. In a sample of junior high school graduates, youth expectations do not seem to matter in the decision to attend senior high school (except in families where fathers are absent, in which case boys' expectations matter), but mothers' expectations about employment still matter for girls. Kaufmann (2012) uses the same data to investigate the income gradient in college attendance in Mexico and concludes that differences in the expected returns of attending college in poor and rich households are not sufficient to explain this gradient. Rather, credit constraints seem important.

Delavande & Zafar (2013) examine the determinants of the type of higher education chosen by students in urban Pakistan and estimate the model described in Section 2. They find that, on average, students accurately perceive differences in relative returns, costs, and academic difficulty levels associated with the different school types. Yet there is substantial heterogeneity in expectations about future earnings and nonpecuniary school outcomes. Importantly, estimates from the choice model show that both future earnings and nonpecuniary school-specific outcomes—including school's ideology and parents' approval—are significant determinants of school choice in this context, where education can be religious or secular. Estimates of choice elasticity with regard to earnings are similar to those obtained for students in the United States and other developed-country settings. The analysis also reveals that credit constraints play a major role in school choice: If awarded a scholarship financing school fees and boarding, one-third of the students would enroll at a school different from their current institution. Interestingly, Madrassa students—the group for whom credit constraints are most binding—are relatively less likely to switch schools. Ideology is likely to be an important factor for them in their choice. The authors also simulate the impact of an information campaign providing data on actual returns to schooling and find that, in this sample of motivated students already pursuing a bachelor's-equivalent degree, gains from such a campaign would be small, as perceptions of returns are quite accurate.

[5]Data from the minimum, maximum, and midpoint are fitted to a parametric distribution. The expected and variance of log earnings are then computed from this fitted distribution.

This review focuses here on studies using probabilistic expectations, but it is worth mentioning briefly two related papers that look at the influence of information provision about future earnings on expected earnings (as a point estimate, rather than a full distribution) on schooling outcomes (Nguyen 2008, Jensen 2010) because both point out that students and parents tend to be misinformed about the returns to education and that providing information improves school outcomes. Jensen (2010) finds that the returns to secondary schooling perceived by students in the Dominican Republic are extremely low, while the measured ones are high. Students from randomly selected schools were informed of the returns estimated from earnings data. The perceived returns of all students increased when re-interviewed 4–6 months later. And 4 years later, those from households with higher income had completed significantly more schooling, suggesting that both a lack of information and credit constraints are important. Nguyen (2008) uses a similar approach in Madagascar and finds that providing statistics on actual returns improves test scores, particularly for those underestimating the returns.

4.3. Input and Output in Agricultural Production

Rural households living from agricultural production face substantial income fluctuations owing to input and output price variation, weather shock, or land tenure insecurity. I review here a series of work on expectations relevant to agricultural production.

Rainfall is an important input in agricultural production and is rather variable. Luseno et al. (2003) and Lybbert et al. (2007) ask pastoralists in Ethiopia and Kenya to provide probabilistic seasonal rain forecasts. They find that pastoralists have reasonably accurate perceptions of rainfall. They also investigate whether receiving information from modern model-based climate forecasts leads to a revision of expectations. The minority of pastoralists who receive those forecasts updated their expectations for below-normal rainfall but not for above-normal rainfall, suggesting that updating is asymmetric between rainfall states.[6] However, receiving the forecast had little impact on behavior. Giné et al. (2009) ask respondents in India the likelihood that the monsoon season would start in various time periods. Planting at the right moment relative to the onset of the monsoon season is crucial for crop success. They find that Indian farmers who believe the monsoon season is likely to start later are more likely to plant later, less likely to replant, have purchased a lower share of total production inputs before the onset of the monsoon season, and are more likely to buy weather insurance, even after controlling for a wide range of farmer characteristics, including proxies for risk aversion and discount rates. The authors also find that farmers who have less access to risk-coping mechanisms have more accurate beliefs.

Another set of work focuses on prices and the output of agricultural production. Dillon (2012) elicits subjective distributions of end-of-season cotton yield and prices from cotton farmers in Tanzania. He estimates a dynamic stochastic model of cotton production. The availability of the subjective distributions enables the identification of both plot fixed effects and plot-specific shock distributions. The estimated heterogeneity in plot quality and plot-level risk (which is usually farmers' private information and not identified in models that do not use subjective expectations data) is large enough to offer plausible explanations for two puzzles related to agricultural policy in developing countries: the lack of private markets for crop insurance (owing to adverse selection) and the small impact of the provision of price information (because price risk is too small to induce input reallocation). Hill (2009) collects subjective distributions of coffee prices from coffee

[6]The provision of information is nonexperimental, and only 15% of the respondents heard the forecast. Respondents are also not asked priors and posteriors. Rather, priors are estimated and posteriors observed.

farmers in Uganda, along with risk preferences. She finds that the perceived probability of a negative return (i.e., the probability mass allocated in the bottom intervals of the elicited distribution) is associated with a lower share of labor allocated to coffee production.

Maertens (2012) seeks to understand the role of social networks in the adoption of a new technology in India: Bt cotton, a new type of genetically engineered cotton. Because it is supposedly relevant to the adoption decision, she elicits the expected cotton yield distribution conditional on using Bt cultivar and on using non-Bt cultivar (and also conditional on soil characteristics, irrigation status, and expected input use). She finds that a higher difference in expected yield (Bt versus non-Bt) and a decrease in the variance of non-Bt yield are associated with a higher likelihood of planning to cultivate Bt cotton. Also, having observed more progressive farmers who adopted Bt cotton in one's network is negatively associated with the variance of the perceived yield of Bt cotton.

In a series of papers, Bellemare (2009a,b, 2012) seeks to understand why reverse share tenancy (that is, a sharecropping contract between a poor landlord and a rich tenant) accounts for a large share of rental contracts in Madagascar. Despite being less efficient than fixed rent contracts, sharecropping is typically thought of as being chosen by a risk-neutral landlord to extract more surplus from a risk-averse tenant (Ray 1998). However, local customs in Madagascar are such that the party who bears the risk in agricultural production and takes possession of the land output could claim the land as its own. Bellemare (2009b, 2012) therefore speculates that tenurial insecurity is an important driver of land tenancy contracts. To test this hypothesis, he elicits landlords' subjective probability of losing their claim to the land under the current contract and the other (hypothetical) contract. Those tenurial insecurity probabilities tend to be small (less than 2% on average) but are larger under fixed rent than under sharecropping contracts. Moreover, the difference in tenurial insecurity probabilities predicts the type of contract chosen by a landlord, which is consistent with the hypothesis that weak property rights are important to explain reverse share tenancy.

4.4. Income and Wealth

Low income and wealth are important features of developing countries. A couple of papers elicit income and wealth expectations directly. Attanasio & Augsburg (2012) ask individuals in rural India their subjective distribution of income in the coming year. After doing several checks to verify the data quality, the authors use the elicited subjective expectations to characterize the income process faced by households. This approach is an alternative to using dynamic panel data methods to characterize the stochastic properties of income processes. They find that households face a persistent income process and that the hypothesis of random walk cannot be rejected.

Two papers evaluate how earnings expectations influence either migration choice (McKenzie et al. 2013) or occupational choice (Keats 2013). McKenzie et al. (2013) elicit income and employment expectations in New Zealand from individuals currently residing in Tonga, including winners and losers of a lottery to which Tongans can apply to gain the right to migrate to New Zealand. Although there is a general concern that potential migrants would be overly optimistic about the economic prospects abroad, the authors find that potential male migrants underestimate both the odds of being employed and earnings conditional on working, while potential female migrants have accurate expectations. This underestimation appears to be driven by inaccurate information flows from extended family residing in New Zealand who may claim to be earning less than they actually are to mitigate the pressure to send large remittances and by the gender wage premium being much higher in New Zealand. The income expectations are also positively and significantly associated with the decision to apply to the migration lottery.

Keats (2013) investigates how individuals in rural Kenya choose additional income-generating activities that supplement earnings from subsistence farming, with a focus on the role of (the lack of) access to credit and insurance. He elicits expected entry cost and the subjective distribution of profit for 16 nonfarm occupations as well as farming. People seem to have reasonably accurate beliefs about entry cost and profit. Interestingly, respondents associate higher profit with greater risk. The author then combines the expectations data with data on occupations to estimate a random utility model of occupational choice where the utility is assumed to depend on the log of the average profit, the log of the variance of the profit, and the entry cost of an activity. Individuals are more likely to choose occupations with higher profit and lower risk, while entry cost seems irrelevant to the decision. This suggests that the lack of insurance (rather than the lack of access to a credit market) prevents entry into high-profit but high-variance occupations.

Santos & Barrett (2011) elicit wealth expectations from pastoralists in southern Ethiopia and seek to explore the consequences of nonlinear wealth dynamics for the formation of bilateral credit arrangements. In particular, they elicit subjective expectations of herd dynamics. Respondents were asked to predict their distribution of herd size 1 year ahead, conditional on randomly assigned hypothetical initial herd size and rainfall scenarios. Doing some simulations, the authors find that herders' expectations of herd size match well the nonstationary herd dynamics that herd history data would suggest. In particular, those with smaller herds are forced to stay near their base camp, where spatial concentration leads to rangeland degradation and thus a further decrease of herd size. As a result, there is a threshold below which herd size tends to converge to a low-level stable size and above which it can grow toward a high-level stable size. The authors use these data to generate expected gains from lending one animal and the expected capacity to repay a loan and seek to predict a herder's willingness to lend to a randomly selected herder in their data. Among matches who experienced losses of cattle in the recent past, those who are just below the predicted threshold in terms of herd size are more likely to receive a loan than those above the threshold, providing a safety net against a collapse in the bad equilibrium. Among matches who did not experience losses of cattle in the recent past, those with higher expected capacity to repay and those with larger herd size are more likely to receive a loan. Overall, this seems to suggest a process of social exclusion and a poverty trap for pastoralists with low herd size.

4.5. Expectations About the Impact of Programs by Experts

Professional forecasters have long been asked to provide expectations in developed countries (sometimes only in the form of point predictions of future events). In the US context, for example, the Survey of Professional Forecasters asks macroeconomic forecasters to provide point and probabilistic predictions about future GDP growth and inflation. In a series of papers, Groh et al. (2012), de Andrade et al. (2012), and Hirshleifer et al. (2012) ask professionals, policy makers, and academics about their expectations for the impact of some interventions before the results are known. The motivation is that, once the impact of an intervention has been evaluated, it is often easy for policy makers or academics to claim ex post that, whatever the impact, it was obvious and expected ex ante (see discussion in Groh et al. 2012). Their results show that the impacts are generally not expected by experts ex ante and that there is uncertainty related to them.

I discuss Groh et al. (2012) in greater detail here. The authors examine the impact of a randomized experiment in Jordan in which female community college graduates were assigned to receive a wage subsidy voucher, soft skills training, both, or nothing. The wage voucher led to a 40–percentage point increase in employment in the short run, but the average effect is much smaller and no longer statistically significant after the voucher period has expired. After providing details on the program, the authors asked academics and Jordanian policy makers their expectations about the impact of such a program. The results reveal considerable uncertainty. Moreover, the impact of the voucher (soft skills training) is larger (smaller) than most people would expect. There was also considerable heterogeneity among respondents in their relative rankings of the various interventions.

5. CONCLUSION

This review points to a recent but growing literature using probabilistic expectations elicited from survey respondents in developing countries. Along with earlier reviews (Attanasio 2009, Delavande et al. 2011b), it confirms that it is feasible and useful to ask probabilities in surveys in low-literacy settings. In both developed and developing countries, additional innovations in the elicitation method may improve data quality. But, in my view, it is now time to collect and use these data more comprehensively to improve our understanding of how people make decisions and how policy may change their behavior. Although the literature in developed countries has focused heavily on validation of these data, the current, and admittedly small, literature in developing countries (maybe because it builds on this former literature) seems to have moved on already and has embraced the use of those expectations to understand important policy-relevant topics related to health, education, migration, and income generation, among others.

Development economists are heavily involved in data collection, and many interventions combined with surveys are rolled out all over the world. It therefore seems worthwhile to elicit expectations as part of those surveys when feasible to better understand why a particular intervention was successful or not. Existing studies point out the usefulness of expectations data for identification purposes. This is not to say that using expectations data does not require any assumptions. In some contexts, endogeneity issues (because unobservable characteristics may influence both belief formation and behavior) may be of particular concern. Yet fewer assumptions are required with than without those data to make inferences on behavior.

Several studies reviewed in this article have simulated how behavior would change if beliefs changed, for example, owing to (hypothetical) information campaigns. Those results are interesting and may point toward the type of information that will be more successful at changing behavior. But these simulation exercises require assumptions on how providing information would change beliefs. Given the heterogeneity in beliefs that is observed in the data for all types of outcomes, it is likely that individuals use different updating rules and would end up with different beliefs when receiving the same information. Overall, more work is needed to understand how individuals form and revise their expectations in the field. Also, particularly because it is likely to be relevant to the revision process, it may be useful to measure how certain people are about their reported beliefs, for example, by asking a range of probabilities (as in Manski & Molinari 2010). I am not aware of similar attempts in a developing-country context.

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