Journal of Health Economics 27 (2008) 1095–1108

Contents lists available at ScienceDirect

Journal of Health Economics

journal homepage: www.elsevier.com/locate/econbase

Bias and asymmetric loss in expert forecasts: A study of physician prognostic behavior with respect to patient survival

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ARTICLE INFO

Article history:
Received 23 November 2006
Received in revised form 1 February 2008
Accepted 10 February 2008

JEL classification:
I10, I12, I19, D01, D80, C53

Keywords:
Loss function
Forecasting
Behavioral economics
Survival
Prognosis

ABSTRACT

We study the behavioral processes undergirding physician forecasts, evaluating accuracy and systematic biases in estimates of patient survival and characterizing physicians' loss functions when it comes to prediction. Similar to other forecasting experts, physicians face different costs depending on whether their best forecasts prove to be an overestimate or an underestimate of the true probabilities of an event. We provide the first empirical characterization of physicians' loss functions. We find that even the physicians' subjective belief distributions over outcomes are not well calibrated, with the loss characterized by asymmetry in favor of over-predicting patients' survival. We show that the physicians' bias is further increased by (1) reduction of the belief distributions to point forecasts, (2) communication of the forecast to the patient, and (3) physicians' own past experience and reputation.

In this paper, we investigate the accuracy of physicians' forecasts of survival. We ask whether a physician's prognosis exhibits systematic biases, and we explore the sources of such biases. Our investigation uncovers a systematic tendency of physicians to overpredict their patients' survival at three stages: first, with respect to the survival distributions that doctors construct, second in their summarization of this distribution through the selection of a point estimate, and third in their choice about how to further modify this estimate during communication.

The strategic role of communication between physicians and patients has been studied by Caplin and Leahy (2004), illustrating how the standard model of preferences breaks down once agents draw psychological utility from their beliefs. Extending this model, Koszegi (2006) also used physician–patient communication to investigate how provision of information by experts becomes distorted in the presence of anticipatory feelings. These important theoretical contributions lay the groundwork for empirically examining the systematic tendencies of physicians to distort their prognosis when both formulating it and communicating it to their patients.

More specifically, findings from the literature on emotional agency lead us to expect that a closer relationship between a physician and a patient should be associated with more upwardly biased loss. In this model, the physicians' utility function includes their patients' emotional status, therefore providing an incentive for physicians to formulate an upwardly biased prognosis. This theoretical framework also sheds light on why we would expect a doctor to be even more upwardly biased when communicating than when formulating an expectation. It is clearly more emotionally stressful to share bad news than merely to think about it. Additionally, communication provides for a strategic environment consistent with

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doi:10.1016/j.jhealeco.2008.02.011

Koszegi's (2006) model, whereby a physician has an opportunity as an agent to affect the emotional state of the patient as a principal.

Furthermore, as Koszegi (2003) indicates, physician–patient communication may be accompanied by deeper psychological biases such as Samuelson's (1963) fallacy of large numbers—simply defined as accepting a large number of unfavorable gambles even when the agent is unwilling to take any one individual gamble on its own. In fact, some of the classic biases in behavioral economics have been first characterized by studying physician behavior. These are most notably associated with the process by which physicians formulate diagnosis, and they most famously include the role of hindsight in distorting probability estimates (Arkes et al., 1981; Slovic and Fischhoff, 1977), base rate neglect (Casscells et al., 1978; Kahneman and Tversky, 1973), and the conjunction fallacy (Tversky and Kahneman, 1983). In all of these situations, agents produce inaccurate probability estimates given the uncertainty they face over the true state of the world.

The key question that arises here is how physicians understand and process the information about their patients' likelihood of survival, and how they use their own subjective belief distributions to formulate a point forecast. In other words, even before the strategic component of physician–patient communication enters the picture, we can ask whether systematic biases characterize the process by which physicians arrive at their own best point forecast of patients' survival.

In analyzing the asymmetry of physicians' prognosis, it is useful to draw on the broader economic literature on expert forecasts. In one of the first studies of asymmetric loss in economics, Varian (1974) documented an important fact that experts in a market face different costs depending whether their best prediction is an overestimate or an underestimate of the market price. In his study of the market for single family homes in a 1965 California town, Varian noticed that assessors faced a significantly higher cost if they happened to overestimate the value of a house. While in the case of an underestimate, the assessor's office faced the cost in the amount of the underestimate, conversely, in the case of the overestimate by an identical amount, the assessor's office faced a possibility of a lengthy and costly appeal process. Since this classic study, loss functions have become an important aspect of the study of expert forecasts.

The two key empirical puzzles surrounding the question of expert forecasts became to determine whether forecasters' loss functions were symmetric, and if not, how optimal forecasts can be made given loss asymmetry, as addressed most recently by Elliott et al. (2005). For example, government experts making budget forecasts may be influenced by political incentives, as the costs of wrongly projecting a surplus may lead to public disapproval, while wrongly projecting a deficit may lead to an impression of exceptional government performance. Artis and Marcellino (2001), as well as Campbell and Ghysels (1995), document that budget deficit forecasts have asymmetric loss. Furthermore, expert opinion varies greatly and systematically. For example, research by Lamont (1995) indicates that factors such as forecasters' experience and reputation are reliable determinants of experts' willingness to deviate from consensus forecasts of GDP, unemployment, and prices.

In financial and macroeconomic forecasting, Granger and Newbold (1986) have concluded that economic theory does not suggest that experts even should have a symmetric loss function. An improved understanding of behavioral biases arising in agents' decisions, such as those associated with loss functions, can contribute to answering puzzles about risky behavior in the labor market and education decisions (e.g., Abowd and Card, 1989; Card and Hyslop, 1997; Card and Lemieux, 2001a,b) and in health economics (e.g., Koszegi, 2003, 2006).

Because in most economic situations, such as Varian's (1974) real-estate market, agents formulate and report point predictions as their forecasts, the agents' true subjective belief distributions are lost and cannot be recovered from their forecasts. Hence the problem of characterizing the loss function is compounded by the fact that we do not know anything about the behavioral process by which agents reduce their belief distributions into single-point predictions, a process which itself reflects the extent of asymmetry in their unobserved loss function. Furthermore, because of strategic considerations, the prediction that agents communicate may be different from both the point prediction and the prediction implied by the agents' full subjective belief distributions. Unfortunately, due to data limitations, no study has been able to examine all of these aspects of forecasting simultaneously. To date, the study of loss function asymmetry has been largely limited to studying point forecasts (e.g., the Livingstone survey), while the study of forecasters' fuller subjective belief distributions has been confined to surveys of national output by experts (e.g., Survey of Professional Forecasters), as illustrated by the work that originated with Victor Zarnowitz's (1985) study of rational expectations.

Our study addresses the extent of intrinsic bias in forecast predictions and asks how the forecast bias and the symmetry of the loss function change as agents move from a full subjective distribution to a point prediction and then to communicating their formulated forecast. We focus on the first part of the processes because psychological research by Tversky and Kahneman (1973, 1974) has documented that individuals exhibit different types of biases when using probability distributions to infer a possibility of an outcome. Analogous to the biases that arise from the use of inference heuristics such as representativeness or availability, agents may also exhibit biases when narrowing their subjective belief distributions to single-point predictions. In particular, because the standard symmetric loss function requires minimization of the mean squared error, individuals may show systematic bias due to failure to compute a correct mean or because t have asymmetric loss. Much like econometric estimators that are biased when certain assumptions fail, the behavioral mechanism leading to a point forecast from subjective beliefs may be biased due to computational limitations or a misinterpretation of the optimization problem by agents. We also focus on the latter part of the process – the role of communication – because, with the exception of independent, disinterested expert forecasters, the communication of an agent's forecast is likely to play a strategic role in a market. Therefore, any bias that led to formulation of the forecast may be further compounded by the agent's strategic biases in communicating the prediction. To study all of this, we need a record of forecasts that documents both the process of reduction from subjective beliefs to a point forecast and the process of communication of that forecast.

To investigate the problem, we use a unique prospective study of Chicago metropolitan area physicians referring terminally ill patients to hospice care. To our knowledge, this is the first survey that collected a combination of forecasts allowing us to study all the aspects of the above question. First, the study asked physicians to make interval forecasts of the patients' survival probability, approximating a subjective belief distribution. Second, the physicians' best point prediction of survival was recorded. Third, physicians were asked what prediction they would communicate to their patients. Fourth, a series of questions regarding the physicians' confidence, optimism, and experience was recorded, as well as the patients' characteristics. Finally, the prospective nature of the study allowed us to compare the different forecasts to the patients' actual survival time. Together, these features of the data give us a unique opportunity to study loss functions that characterize physician decision-making.

We quantify the extent of asymmetry in how much physicians value over-predicting versus under-predicting their patients' survival. We also demonstrate that the physicians' bias increases when they communicate their prognosis to their patients. The physicians' own loss function becomes more asymmetric, favoring over-prediction of survival, when they move from formulating a point prediction to communicating a prognosis to their patients. We also show that the asymmetry in the physicians' loss function moves in the other direction when a fuller subjective belief distribution is elicited from the physicians. In contrast to the point forecast, the physicians' bias decreases when they forecast a subjective probability distribution over their patients' odds of survival.

We also asked which physician and patient characteristics serve as determinants of the level of asymmetry in the physicians' loss function. Our findings indicate that the patients' gender, race, and type of disease, as well as the physicians' experience, are important determinants. Together, these results point to the fact that physicians may rationally prefer to overestimate survival of their patients. Given the economic and clinical nature of the doctor–patient relationship, overestimating the odds of a patient's survival can be expected to serve as a commitment device to a prescribed choice of therapy and contributes to the physicians' sense of confidence. In the setting of hospice care in particular, evidence of upward bias suggests that emotional agency described above comes to the forefront, playing an important role in physicians' behavior above and beyond the commitment mechanism observed elsewhere. However, the evidence that patients' race and gender play a role in the degree of loss asymmetry indicates that physicians' forecasts are also subject to biases beyond a rational calibration of the loss function.

Because forecasting of patients' survival is an important part of the medical profession (Christakis, 1999), our characterization of physicians' loss functions serves two purposes: (1) in general, it carries implications for understanding behavior of experts whose performance depends on forecast accuracy, and (2) more particularly, it has downstream implications for understanding the supply of health care and for health care expenditures.

The paper is organized as follows. Section 1 introduces the data. Section 2 presents the method we use for estimation of loss functions. Section 3 presents the results. Section 4 discusses the conclusions.

1. Data

1.1. Patient and physician data

To study prognostic accuracy and bias among physicians, we use data from a 1996 prospective cohort study, conducted in the Chicago metropolitan area. The study approached all hospices in Chicago that admitted more than 200 patients per year. Five of the six such hospices participated in the study, producing a cohort of all patients admitted during 130 consecutive days in 1996 (Christakis and Lamont, 2000).

For all patients in the study, the physician who referred the patient to hospice care was empaneled (none of the participating physicians were the hospice medical directors). In some cases, the referring physician was the primary care doctor and in others the physician was a specialist (such as the treating oncologist). We collected a prognosis from only one doctor for each patient. We collected individual physician data (e.g., their sex, specialty, year of graduation from medical school, board certification, etc.) and three variables that characterizes the relationship between the doctor and the patient, namely, duration of contact (when they first met), frequency of contact, and recency of contact (when the doctor last examined the patient). All physicians were surveyed at the same point in time, typically within 48 h of the time they referred the patient to hospice.

The descriptive statistics are summarized in Table 1. We studied a total of 504 patients referred by 365 physicians. All patients were followed until their deaths. At the time of hospice referral, all patients were terminally ill. The most frequent diagnoses were lung cancer (18%), AIDS (12%), colorectal cancer (7%), breast cancer (6%), chronic heart failure (5%), and stroke (5%).

The main variables of interest measure the physicians' forecast of their patients' survival. Physicians were surveyed to record three different types of prognosis: (1) the point prediction is an answer to a question about the physicians' best estimate of how long this patient has to live; (2) the communicated prediction is an answer to a question about what prognosis the doctor would communicate to the patient if the patient or the family insisted on receiving an estimate of survival; (3) the subjective distribution prediction is the physicians' stated percent estimate that the patient would still be alive 7, 30, 90, 180 and 360 days after referral. Because we recorded the time of death, we can measure actual survival directly and estimate the accuracy and biases physicians exhibit when they formulate their prognosis.

The explanatory variables analyzed below include: patients' basic demographics (age, gender, race), income (based on the patients' ZIP codes), the duration of the disease that led to their final prognosis, and the Eastern Cooperative Oncology

Table 1
Descriptive statistics

Variable	Mean (S.D.)	Variable	Proportions (%)
Patients			
Age (year)	68.6 (17.4)	Sex (female)	55.4
Household income ($)	33,186 (11,178)	Race (not white)	32.4
Disease duration (days)	83.5 (135.8)	Cancer patients	64.5
ECOG physical activity	2.80 (1.01)		
Physicians			
Hospice referrals (last quarter)	12.3 (16.9)	Sex (female)	19.8
		Speciality (family or GP)	54.8
		Board certification	80.3
		Self-described optimist	73.3
		Graduated from medical school ranked top 10th percentile	17.5
Physician–patient relationship			
Time since first meeting (days)	159 (308)		
Number of contacts in the past 3 months	11.1 (13.9)		
Prognosis and survival			
Point prediction of patient survival (days)	106.6 (123.2)		
Communicated prediction of survival (days)	116.1 (111.0)		
Actual survival (days)	62.2 (104.5)		

Group (ECOG) score (measuring patients' performance status: 0 for normal activity and 4 for completely bed-bound). The physicians' data includes their gender, a dummy for whether a physician has a specialty, a prestige indicator of whether the physicians' medical school was ranked in the top 10th percentile of all medical schools, the number of hospice referrals in the past quarter, and whether the physician considers himself or herself an optimist (based on Seligman, 1991). The time since first meeting is the number of days elapsed since the physician first met the patient, and the frequency of contact is measured as the number of days the physician has seen or spoken with the patient in the last 3 months.

1.2. The subjective belief distribution

Another key feature of the dataset is that it allows us to use the distribution of subjective beliefs to study the bias in how prognoses are formulated and how this bias changes as physicians move in their decision-making from a full belief distribution to a point prediction and then to a communicated prognosis. To study the subjective belief distribution, we focus on the mean. To calculate the mean of the subjective distribution, we used the physicians' interval predictions of the probability that a patient would survive for 7, 30, 60, 180, and 360 days. We assumed that the subjective probability of a patient's survival at day 0 is 100% (i.e. the patient was alive on day 0).

We used a non-parametric approach to obtain a mean of the subjective distribution, given that we had point estimates of the survival probability. The probabilities of survival for every day between 0 and 360 days were interpolated using linear regression, and a lowess regression was then used to smooth our observations, giving us a non-parametric survival function for each patient (as formulated subjectively by the physician). Finally, using this non-parametric survival function, the mean was computed by minimizing the distance between the probability of a patient's survival and the 50% value (using the minimum squared error). This gave us a mean survival probability from the physician's subjective distribution of beliefs over his or her patient's survival.

In Fig. 1, we analyze the relationship of the mean survival resulting from a full subjective belief distribution with three other values: (1) actual survival of the patient, (2) point prediction, and (3) communicated survival. We present a scatter plot, followed by a fractional polynomial regression line with confidence intervals. The advantage of the fractional polynomial regression is that it does not rely on a linear assumption of the relationship between our mean of the belief distribution and the other three variables.[1] We also plot a 45° line to evaluate the extent of symmetry or asymmetry in the relationship.

The results in this figure give us the first indications of the significance and the direction of bias in physicians' prognoses. The physicians' subjective probability distributions are poorly calibrated, as the mean of this distribution over-estimates the patients' actual survival. As physicians move from their subjective distributions to point predictions, this bias increases. We see this because the extent of asymmetry is greater when the point prediction is compared with actual survival than when the belief distribution is compared to actual survival. The same happens when physicians move to the communicated prognosis. Hence, this initial evidence suggests that physicians over-estimate their patients' survival, and that this bias may be further increased as physicians move from a subjective belief distribution to a point prediction and then to a communicated survival.

[1] While many other nonlinear or non-parametric models could be used, the advantage of this approach is that it is easily implemented and that polynomials with a sufficient number of higher-order terms offer a good enough approximation of most well-behaved, continuous functions.

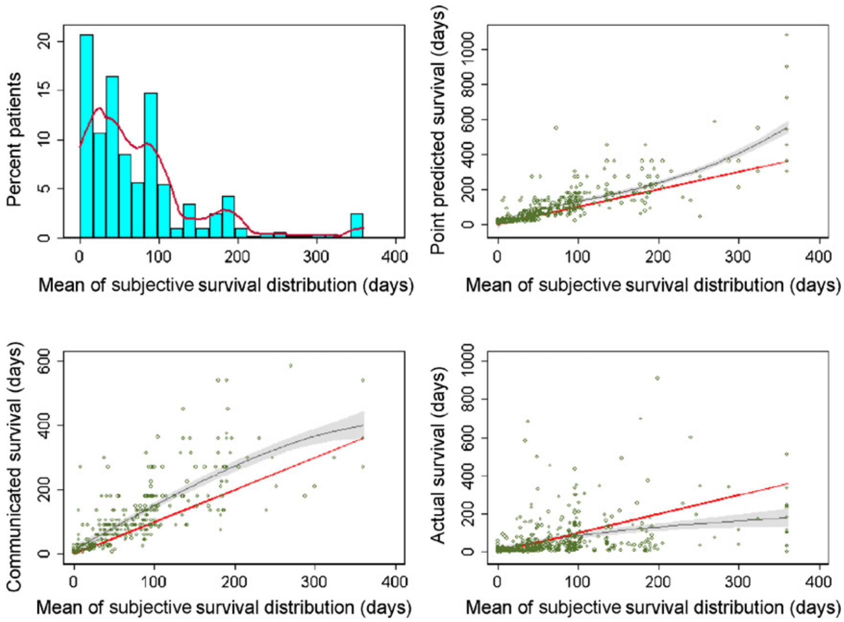

Fig. 1. Physicians' prognosis of patient survival. *Note*: Upper-left to lower-right: (1) Up to the left: The distribution of physicians' predicted survival, based on a mean of their subjective belief probability distribution. (2) Up to the right: The relationship between the mean of the belief distribution and the point prediction of survival. (3) Down to the left: The relationship between the mean of the belief distribution and the physicians' communicated prognosis. (4) Down to the right: The relationship between the mean of the belief distribution and actual survival. Red straight line represents symmetry. The blue curved line is the estimated relationship with 95% CI shaded. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

2. Estimation of the loss functions

Our question in this section is to characterize the shape of asymmetry in the loss function of an average physician in our sample. We use a flexible loss function approach which is then applied to two common forms of asymmetric loss functions in forecasting, the lin–lin and the quad–quad function (Elliott et al., 2003). The general loss function is given by

$$L(p,\alpha)=[\alpha+(1-2\alpha)\times 1(y_i-\hat{y}_i<0)]\times|y_i-\hat{y}_i|^p, \tag{1}$$

where $p\in\mathcal{N}$, the set of all positive integers, $\alpha\in(0,1)$, and $y_i-\hat{y}_i$ is the forecast error.

2.1. An estimation method for the average physician loss function

To estimate the average asymmetry parameter for our physician sample, we use an estimator developed by Elliott et al. (2003):

$$\hat{\alpha}=\frac{(1/N)\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|^{p-1}\times(1/N)\sum_{i=\eta}^{N+\eta-1}1(y_i-\hat{y}_i<0)|y_i-\hat{y}_i|^{p-1}}{(1/N)\left[\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|^{p-1}\right]^2}. \tag{2}$$

For the lin–lin function, $p=1$, and the estimator becomes simply:

$$\hat{\alpha}_{\mathrm{l}}=\frac{\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|^0\times\sum_{i=\eta}^{N+\eta-1}1(y_i-\hat{y}_i<0)|y_i-\hat{y}_i|^0}{\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|^0}=\frac{\sum_{i=\eta}^{N+\eta-1}1(y_i-\hat{y}_i<0)}{\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|^0} \tag{3}$$

and for $\eta=1$, $\hat{\alpha}=\sum_{i=1}^{N}1(y_i-\hat{y}_i<0)/N$

For the quad–quad function, $p=2$, and the estimator becomes:

$$\hat{\alpha}_{\mathrm{q}}=\frac{\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|\times\sum_{i=\eta}^{N+\eta-1}1(y_i-\hat{y}_i<0)|y_i-\hat{y}_i|}{\left[\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|\right]^2}, \tag{4}$$

$$\hat{\alpha}_{\mathrm{q}}=\frac{\sum_{i=\eta}^{N+\eta-1}1(y_i-\hat{y}_i<0)|y_i-\hat{y}_i|}{\sum_{i=\eta}^{N+\eta-1}|y_i-\hat{y}_i|}. \tag{5}$$

Finally, we use bootstrap methods to estimate the standard errors of our parameter estimates.

2.2. Estimation of individual asymmetry parameters

In contrast to the estimators above, in order to obtain an individual loss function parameter, we need to make two parametric assumptions. First, we assume that the loss function follows the LINEX form, following Zellner (1986). For the purposes of clarity of exposition, we follow Zellner's notation in this part that differs only slightly from our notation above. Denote loss by $x = \hat{\theta} - \theta$, where $\hat{\theta}$ is the forecast and θ is the actual realization. The loss is then defined as

$$L(x) = b\mathrm{e}^{ax} - cx - b, \tag{6}$$

where $a, c \neq 0, b > 0$.

The condition for the minimum to exist at $x = 0$ is $ab = c$. Hence, we can rewrite the LINEX function to include a single scale parameter b and a single asymmetry parameter a:

$$L(x) = b[\mathrm{e}^{ax} - ax - 1], \tag{7}$$

where $a \neq 0, b > 0$.

The posterior expectation of the LINEX function is:

$$E_\theta L(x) = b[\mathrm{e}^{a\hat{\theta}} E_\theta \mathrm{e}^{-a\theta} - a(\hat{\theta} - E_\theta \theta) - 1], \tag{8}$$

where E_θ is the posterior expectation with respect to the pdf $f(\theta)$. The value of θ that minimizes this expression $E_\theta L(x)$ is:

$$\hat{\theta}^* = -\frac{1}{a} \ln(E_\theta \mathrm{e}^{-a\theta}), \tag{9}$$

given the standard condition that the moment generating function of $E_\theta \mathrm{e}^{-a\theta}$ exists and is finite.

Next, to obtain a closed form solution for the asymmetry parameter a, we assume that predictions are drawn from an exponential distribution with parameter λ.[2] The optimal estimator then becomes:

$$\hat{\theta}^* = -\frac{1}{a} \ln \frac{\lambda_i}{\lambda_i - a_i}, \quad \text{where } i = 1, \ldots, n. \tag{10}$$

Rearranging the expression, we obtain:

$$a_i = \exp[-\mathcal{L}_W(-\hat{\theta}^* \exp(-\lambda_i \hat{\theta}^*)\lambda_i) - \lambda_i \hat{\theta}^*]\lambda_i - \lambda_i, \tag{11}$$

where $\mathcal{L}_W(\,)$ is the Lambert W function, defined as the inverse of the equation $W\mathrm{e}^W = x$ (Corless et al., 1996; Hayes, 2000).

3. Results

3.1. Is the physicians' loss function symmetric?

Before proceeding to the application of the loss function estimation method to our data, we briefly turn to testing the proposition that physicians exhibit a bias in their prognosis. Consider a general asymmetric forecast loss function in the form:

$$L(\epsilon) = \{a_1\epsilon^2 + a_2\epsilon\}1(\epsilon < 0) + \{b_1\epsilon^2 + b_2\epsilon\}1(\epsilon \geq 0). \tag{12}$$

By assumption, the physicians minimized the loss at each decision. Let $\hat{y}$ be the forecast and let y be the actual realization of the forecasted variable, in our case the patient's survival. Hence:

$$\hat{y} = \underset{\hat{y}}{argmin} L(\epsilon) = \underset{\hat{y}}{argmin} \{a_1\epsilon^2 + a_2\epsilon\}1(\epsilon < 0) + \{b_1\epsilon^2 + b_2\epsilon\}1(\epsilon \geq 0). \tag{13}$$

Using first order conditions, and solving for y (see Appendix A) implies:

$$y = \hat{y} - \frac{2a_2}{a_1 + b_1} - \frac{2(b_2 - a_2)}{a_1 + b_1} 1(\epsilon \geq 0). \tag{14}$$

If all decision makers are assumed to use the same loss function, this suggests running the following regression:

$$y = \alpha + \beta\hat{y}_i + \gamma D_i + e_i, \tag{15}$$

where $D_i = 1 \text{ if } (y - \hat{y} \geq 0) \text{ and } D_i = 0 \text{ if } (y - \hat{y} < 0)$

[2] The exponential distribution is convenient because it is bounded by zero and because it has a simple analytic form for the moment generating function, being the only functional approximation that allows us to analytically derive the parameter of interest. At the same time, the exponential approximation does not have a substantive effect on the results of our estimation.

Table 2
Tests for asymmetry loss

Type of forecast	H_0	Wald test statistic	Accept/reject
Mean of the subjective belief distribution	Symmetric loss	$F_{(2,475)} = 133.28$, $p = 0.0000$	Reject
Point prediction	Symmetric loss	$F_{(2,466)} = 405.32$, $p = 0.0000$	Reject
Communicated prediction	Symmetric loss	$F_{(2,256)} = 356.44$, $p = 0.0000$	Reject

In order to test the hypothesis that the loss function is symmetrical, one needs to test the joint hypothesis $\beta = 1$ and $\gamma = 0$.

We use the Wald test to test the linear restriction that $\beta = 1$ and $\gamma = 0$ jointly. To do this, the parameters of Eq. (3) above are estimated using OLS. The results are displayed in Table 2. The results suggest that there is enough statistical evidence to reject the hypothesis of symmetric loss between any of the three types of forecasts and the observed survival. We now examine the asymmetry of physicians' loss.

3.2. The shape of the physician loss

We present the results of our analysis in Table 3 and Fig. 2 below. We immediately notice the significant degree of asymmetry in loss over forecast errors. Physicians prefer to err by over-predicting rather than under-predicting survival.

As both Table 3 and Fig. 2 illustrate, the degree of asymmetry varies significantly between different types of forecasts. When physicians make a prognosis through a subjective belief distribution, they have the smallest degree of bias. This bias then increases as physicians move to formulating a point prediction, and it increases even further when they communicate their prognosis. In Table 3, this trend is represented by the increase in the asymmetry parameter as we move from the subjective belief distribution to point prediction to communicated prognosis. Fig. 2 illustrates this graphically. The mean of the subjective distribution (in row 1 of Fig. 2) has the most symmetric loss function of the three, indicating the least amount of bias.

Finally, we wanted to take into account uncertainty when comparing the degrees of bias. Fig. 3 uses bootstrap methods to compare the distribution of the point prediction with both communicated prognosis (left) and with the subjective belief distribution (right). We clearly observe that the distribution is shifted towards the right when physicians move from a point prediction to a communicated prognosis. This corresponds to an increase in the asymmetry parameter, and an increase in bias. In contrast, when we compare the point prediction with the mean of the subjective distribution, we observe a shift to the left. In this case, the mean of the subjective distribution is again associated with a lesser degree of bias than the point prediction. The non-parametric Kolmogorov–Smirnov test for equality of distributions indicated that, in both cases in Fig. 3, the difference between the distributions was statistically significant.

As can be clearly seen in the left panel of Fig. 3, the difference in means between point prediction and communicated prediction is approximately 100%. Similarly, but to a lesser extent, the right panel of Fig. 3 illustrates that the point prediction is approximately 50% higher than the mean of the full subjective belief distribution. While the overlap between the two distributions is higher in this case, it is small enough to reject the hypothesis that the two distributions are the same, as described above. Hence, while the results confirm that the upward bias operates on the two separate levels, the results also indicate that the magnitude of the upward bias is larger in the case of strategic communication than in the case of the physicians' internal cognitive process of forming the best point prediction. The results for the lin–lin case are identical to those for the quad–quad case.

3.3. The determinants of bias

Having estimated the physicians' individual loss parameters, we now examine the determinants of this bias on the micro-level. We conducted regression analysis to explain three different loss parameters. The first is the loss parameter estimated by comparing the subjective belief distribution with the actual survival; the second is the loss parameter estimated by comparing the best point prediction with actual survival, and the third one is the loss parameter estimated by comparing the communicated survival to the actual survival. Because of high levels of heterogeneity among physicians, as well as the potentially complex psychological process through which the bias arises, identifying the determinants of physician bias is inherently difficult. Nevertheless, we can rely on important elements of the principal–agent relationship between a physician

Table 3
Estimated asymmetry parameters for the average physician loss function

Type of forecast	Lin–lin $\hat{\alpha}_l$	Quad–quad $\hat{\alpha}_q$
Mean of the subjective belief distribution	0.1953 (0.0216)	0.1730 (0.0296)
Point prediction	0.2175 (0.0191)	0.2321 (0.0351)
Communicated prediction	0.3515 (0.0218)	0.4004 (0.0416)

Note: The asymmetry parameters estimated were obtained using the estimators described in the text, both for the lin–lin and for the quad–quad form. In each case, the type of forecast is compared to the actual survival as a baseline reference. For more detailed description, see the text.

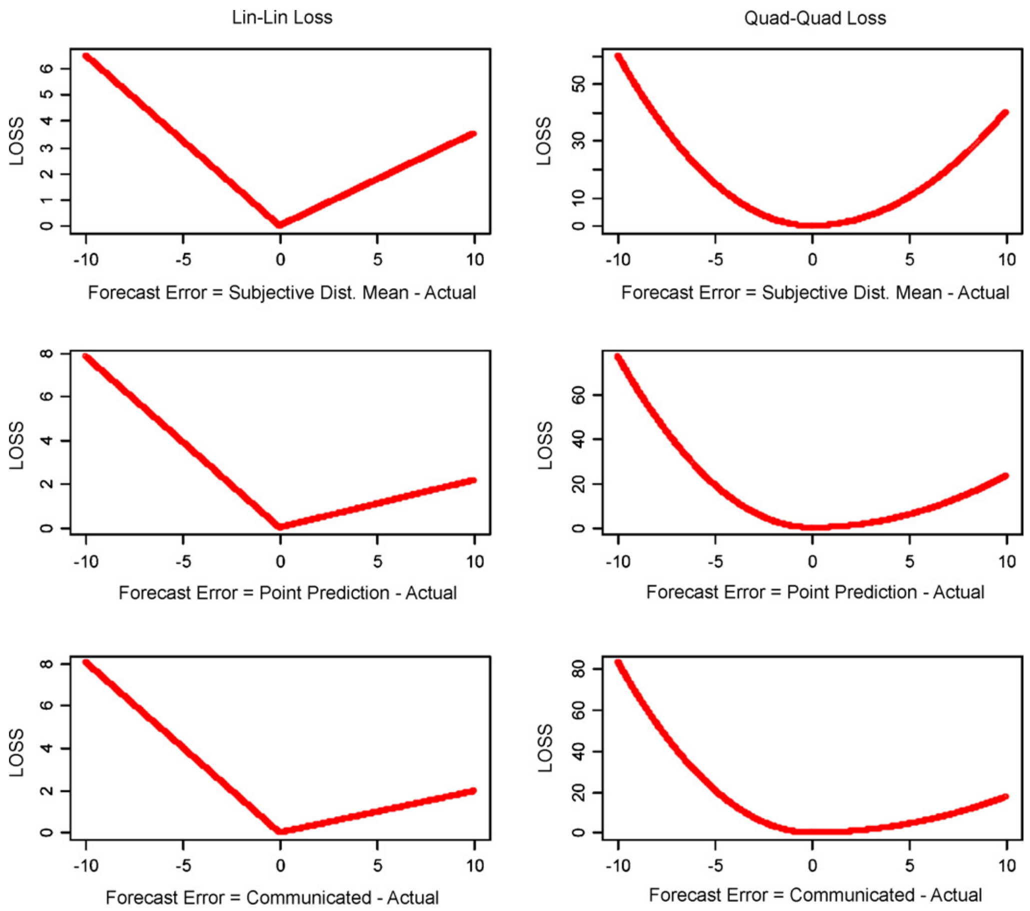

Fig. 2. Estimated average physicians loss functions.

and a patient to develop hypotheses about a few main categories of potential determinants of bias. We can then test these hypotheses to the extent possible with our data.

The starting point for our hypotheses about potential determinants of physician bias are Caplin and Leahy's (2004) and Koszegi's (2003, 2006) theoretical models of psychological games. In a behavioral model of physician behavior, following Koszegi (2006), the physician can be considered as an agent, while the patient is the principal. In the simplest setting, let us assume that the agent maximizes the utility of the principal, but that the principal's utility function has two separate components. The first component is the physical health of the patient, and the second component is the psychological utility from anticipatory feelings. Emotions regarding future well-being are important both because extreme negative emotional

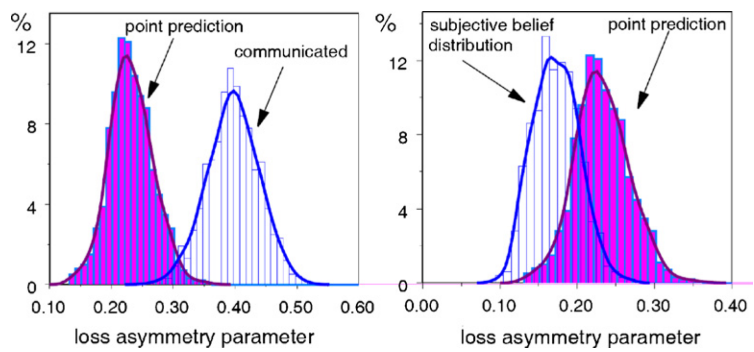

Fig. 3. Distribution of the loss function parameters. *Note*: Illustration of different degrees of asymmetry in point prediction (shaded histograms), communicated prediction (transparent left), and the prediction of patient survival using a subjective belief distribution (transparent right). (1) On the left: An illustration that communication increases bias; (2) On the right: An illustration that the use of the subjective belief distribution decreases bias. The x-axis represents the estimated quad–quad asymmetry loss function parameter. The distributions were obtained by using using bootstrap ($n = 1000$).

states may affect patients physiologically, and because patients place a value on an emotional state (also a component of quality of life generally) independently of physiological effect. After an agent obtains the information about the principal's condition, she formulates the prognosis and communicates it to the principal. The key feature of the model is that communication is strategic in nature; the agent manipulates the expectations of the principal in order to maximize the principal's overall utility function.

In this principal–agent setting, we can now develop three different categories of determinants affecting the physicians' asymmetric loss in respect to prognosis: patient-referential bias, clinical information bias, and physician-referential bias. Because the agents maximize their principal's utility, and the principal's utility is a function of his own personal characteristics, we can expect that the agents' strategic decisions will be conditional on the characteristics of the agent. Furthermore, even if the physicians did not know exactly how the patient characteristics affect patient utilities, physicians as agents form beliefs regarding different patient populations. In empirical terms, this would mean simply that certain categories of patients could be expected to be more likely than others to receive a biased prognosis. Basic demographic categories that affect discrimination in the labor market and education, for example, can be expected to induce a biased prognosis. Most importantly, these would include gender, race, and income.

Additionally, in the principal–agent model, agent behavior is dependent on the quality and the content of the information she receives and can manipulate before she communicates it to the principal. As a result, we can expect that clinical information serving as the basis for prognosis will also influence physician bias. Under the second category of clinical information bias, we can expect factors such as disease history, diagnosis, and physical performance of the patient to affect the bias in physicians' prognosis. Hence, our regressions include as explanatory variables: age, a dummy for any type of a cancer diagnosis, disease duration, and the ECOG score. Our hypothesis here is that more clinical information will help physicians make a more accurate prognosis, driving down their tendency to over-predict their patients' survival. We can expect that the more negative information they have about their patients' clinical condition, the less likely are they to over-estimate survival. Also, certain diseases such as cancer may be better understood (in terms of their prognostic properties) by physicians than other diagnoses such as congestive heart failure.

Finally, by trying to model heterogeneity among physicians, we may be able to find more about the determinants of bias. In a principal–agent relationship, we can expect the ability, willingness, and effort of the agent to maximize the principal's utility to be a function of the agent's personal characteristics. Therefore, under the third category of physician-referential bias, we expect that certain physician characteristics might drive prognostic bias. Our independent variables include the physicians' gender and a series of both subjective and objective measures of the physicians' experience: a dummy for whether a physician has a specialty, a prestige indicator of whether the physicians' medical school was ranked in the top 10th percentile of medical schools, the number of hospice referrals in the past quarter, and whether the physician considers himself or herself an optimist.

In this third category of physician-referential bias, we also include two direct measures of the patient–physician interaction. The number of days elapsed since the physician first met the patient measures the length of their clinical relationship. The number of days the physician has seen or spoken with the patient in the last 3 months measures the frequency of patient–physician contact. Overall, one would expect that as both length and intensity of the physician–patient relationship grow, the bias in survival forecast would change. However, there are two potential conflicting influences—on one hand, the physician will have more information the more he or she sees the patient, but, on the other hand, the physician will develop a stronger personal relationship with the patient that could drive the bias in the opposite direction.

As these last few factors indicate, our groups of hypotheses are not mutually exclusive and a substantial overlap may exist between them. A patient characteristic such as age may affect the psychological utility function of a patient (patient-referential category), but the same characteristic may also provide objective information about the disease condition (clinical information category). Similarly, a physician characteristic such as speciality or prestige may both explain the variance in physicians' ability or willingness to affect their patients' emotional states (physician-referential category) or their ability to process or understand the information about the patient's health status (clinical information category). Regardless of the accuracy of our categorizations, our findings can help reveal whether and how these individual factors affect physicians' prognostic bias.

Our estimation uses OLS with heteroscedasticity-robust standard errors and clustering on physicians (some physicians have more than one patient in the sample). We estimated four different models for each of the three dependent variables: subjective belief distribution mean, point prediction, and communicated prognosis. The models (1) tested the patient-referential bias by including only patient demographic characteristics; (2) tested the clinical information bias by including only clinical history of the patients; (3) tested the physician-referential bias by including only the physician characteristics; (4) tested all three types of hypotheses in a single regression. The results of the last set of models, inclusive of all explanatory variables, are presented in Table 4 for our three dependent variables, respectively. A negative coefficient signifies that the explanatory variable increases the extent of bias in favor of over-prediction. A positive coefficient corresponds to a more accurate prognosis, with a more symmetric loss function.

Neither race nor gender seems to be a consistently strong predictor, although individual characteristics collectively explain a great deal of the variance in the outcome variable. Holding all other measures constant, women tend to receive a more biased prognosis. The race of the patient emerges as significant only in the bias associated with the full subjective distribution, and marginally significant (at 10%) in the bias in point prediction. Nonwhite patients, including African Americans and Latinos, receive more biased prognosis in this case, suggesting that race may influence the behavioral process underlying the reduction

Table 4
Analysis of the determinants of physician bias

	Dependent variable		
	Subjective belief asymmetry	Point prediction asymmetry	Communicated prognosis asymmetry
Patient characteristics			
Sex (female)	−0.590 (0.435)	−0.814** (0.409)	−0.864** (0.337)
Race (nonwhite)	−0.981** (0.454)	−0.677* (0.395)	−0.629 (0.426)
Age	−0.008 (0.013)	−0.001 (0.011)	−0.004 (0.012)
log (income)	−0.703 (0.511)	−0.671 (0.499)	−0.609 (0.497)
Clinical conditions			
Cancer	1.450** (0.542)	1.547** (0.534)	1.073** (0.532)
Disease duration	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)
Physical performance	1.072** (0.203)	1.017** (0.191)	0.954** (0.203)
Physician characteristics			
Sex (female)	−0.787 (0.794)	−0.791 (0.782)	0.521 (0.448)
Specialist	0.375 (0.594)	0.627 (0.561)	−0.012 (0.468)
Board certified	0.079 (0.756)	0.254 (0.741)	−0.565 (0.488)
Prestige	0.654 (0.609)	0.458 (0.595)	−0.117 (0.719)
Hospice referrals	0.015** (0.007)	0.015** (0.007)	0.013 (0.007)
Optimist	−0.039 (0.444)	−0.151 (0.425)	−0.360 (0.408)
Time since meeting	−0.0001 (0.0007)	−0.0004 (0.0007)	−0.00005 (0.00068)
Number of contacts	−0.010 (0.011)	−0.007 (0.011)	−0.0017 (0.023)
Constant	2.528 (5.154)	1.540 (5.055)	3.004
R^2	0.1301	0.1373	0.1540
N	313	307	242

Note: *significance at $p = 0.10$; **significance at $p = 0.05$ level; standard errors in parentheses.

of the fuller subjective belief distribution into a forecast. In contrast, gender plays a more important role in point prediction and communicated prognosis; in these two types of forecasts, doctors are more likely to over-predict survival of their female patients by a greater degree compared to their male patients.

Using the same set of potential determinants of bias, we analyzed further the asymmetry in the loss function as the physicians move from the subjective belief distribution to the point prediction and from the point prediction to the communicated prognosis. In the case of moving form the subjective belief distribution to the point prediction, we find that the patients' race, cancer diagnosis, and ECOG score are all statistically significant predictors of bias ($p < 0.05$, $R^2 = 0.2512$, $N = 322$). The physicians' bias increased when patients were not white, when they had diagnoses other than cancer, and when their physical condition was better. These findings are suggestive of the fact that the physician's prognostic estimates may be incorporating patient preferences and expectations even before the physician communicates the prognosis to the patient. In the case of moving from the point prediction to communicated prognosis, we found that the patients ECOG score was the only statistically significant determinant of the loss asymmetry ($p < 0.0001$, $R^2 = 0.1421$, $N = 254$). As in the previous case, the asymmetry in the physicians' loss function is inversely related to the patients' physical activity; the better the patients perform physically, the greater the physician's bias arising from the communication of the prognosis to the patient.

Our regression analysis provides more consistent evidence in favor the second type of bias we hypothesized: information bias and physician-referential bias. Cancer patients receive less biased prognosis regardless of the form by which the prognosis is made—through a subjective distribution, a best point prediction, or through a communicated prognosis. This conclusion indicates that prognostic bias is dependent on the knowledge physicians have about the diseases they encounter, as well as perhaps on the frequency with which these diseases occur. The level of physical activity is also one of the strongest predictors of physicians' bias. When the patient is physically active, and able to function with little assistance on a daily basis, the physicians' prognosis becomes more inaccurate and doctors inflate the estimates of their patients survival.

Finally, we also uncover evidence that objective indicators of physicians' experience affect prognostic bias. The more hospice referrals doctors make, the less likely they are to make biased predictions of their patients' survival. This holds for the forecasts that involve the subjective belief distribution and the best point forecast, but not the communicated prognosis. However, objective measures of physician quality, such as the prestige of their medical school, are not good predictors of the bias. This finding links to the information bias hypothesis, supporting a classical principle that increasing the amount of information and practical experience with the forecasting problem reduces systematic bias. This suggests that the physicians are Bayesians with biased priors.

To illustrate our findings, Fig. 4 displays the predicted degree of bias for each of the three types of forecasts and focuses on five main determinants of bias in each case. Looking at the point predictions first (row 2), we see that these forecasts are more biased when patients are women, when their diagnosis is other than cancer, when they are in a relatively good condition, and when physicians are relatively less experienced. The situation is similar when we look at bias that arises with communicated prognosis, with the main difference being that the marginal effect of physician experience disappears and the marginal effect of cancer (row 3) on the bias becomes less dramatic. This seems to suggest that information-relevant categories are less important when physicians make decisions on what forecast to communicate to their patients, while patients' gender and physical status have larger marginal effects. Finally, when it comes to the subjective belief distribution,

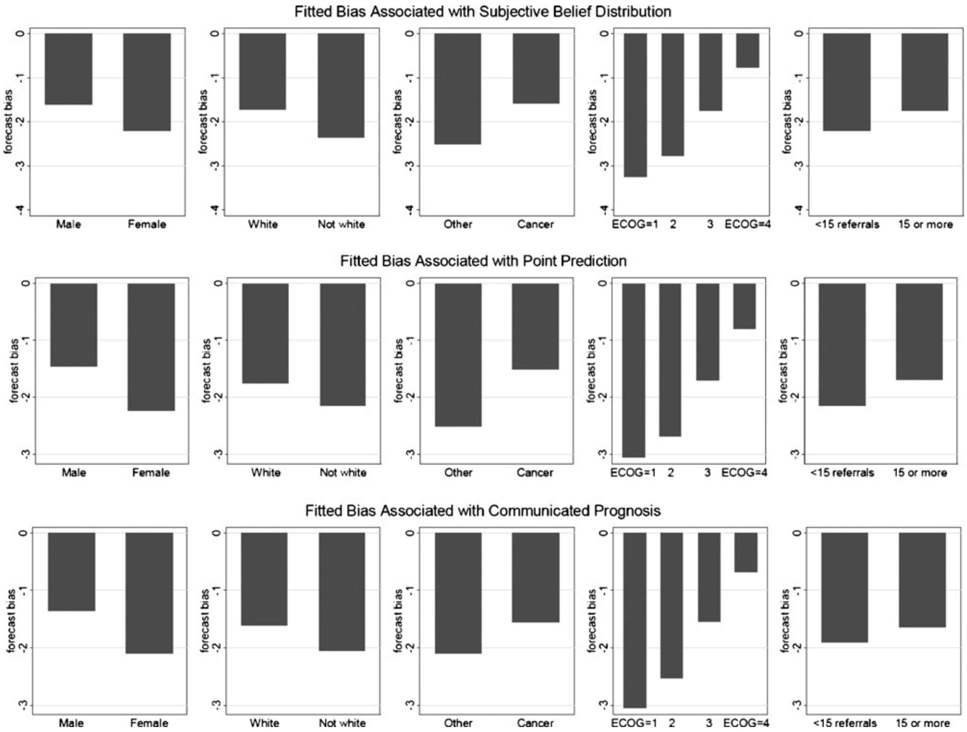

Fig. 4. Estimated effects of patient characteristics and physician experience on bias in prognostic behavior.

Fig. 4 (row 2) illustrates somewhat smaller marginal effects across the four categories. Interestingly, in this case, physicians' bias is also driven by patients' race, in addition to diagnosis type, physical activity, and physician experience.

4. Discussion

We have found that physicians exhibit systematic biases and asymmetric loss in their prognostic behavior, favoring over-predicting their patients' survival. Furthermore, this bias occurs at several levels and it is related to attributes of the patient and the physician. Importantly, we documented the processes by which physicians' forecasting bias is inflated. We found that the bias exists at baseline and that it increases when doctors move from a fuller subjective belief distribution to a point forecast. Most important, we have empirically characterized the loss function of a large sample of physicians. And we find that the asymmetry in physicians' loss function seems to increase as forecasts move from the domain of subjective beliefs to a single-point prediction to the domain of communication. The unique structure of our data allowed us to decompose the forecasting bias, in part providing systematic empirical evidence in support of the models of Ameriks et al. (2003) and Koszegi (2006) that imply experts' communication leads to distortions in the information provided. The most inaccurate prognosis is made when doctors are asked to communicate the prognosis to their patients. This evidence suggests the need to further study the role of the full subjective belief distribution in physician behavior—and in expert forecasting more generally.

However, the evidence we uncovered goes beyond the strategic concerns of communication. Adding to the line of research on physicians' understanding of different aspects of probability and uncertainty (Arkes et al., 1981; Slovic and Fischhoff, 1977; Casscells et al., 1978; Kahneman and Tversky, 1973; Tversky and Kahneman, 1983), our study has documented how biases arise when experts reduce their subjective belief distributions into point forecasts and are then asked to communicate these forecasts to interested parties. We also identified heterogeneity across our sample, identifying gender, race, information, and experience as some of the drivers of this bias.

Our findings have direct implications for understanding asymmetric loss as a form of overconfidence. Psychological experiments suggest that, in presence of high levels of uncertainty, small probabilities are overestimated, large probabilities are underestimated, people anchor their responses to reference magnitudes, and response contraction bias inflates the estimates when outcomes are particularly uncertain (Lichtenstein and Fischhoff, 1977; Fischhoff et al., 1980; Lichtenstein et al., 1982; Poulton, 1989). All these may contribute to the apparent overconfidence of the physicians in our study. Our evidence suggested that increasing the provision of information to the physician and also having more experienced physicians are two separate features that make the forecast loss function more symmetric, effectively driving down apparent overconfidence. However, more information is not sufficient to make the physicians' loss function symmetric and their forecasts rational in the classical sense. Even when uncertainty over an outcome diminishes, two sources of bias remain: reducing a full belief distribution to a single-point forecast and the influence of perceptions over gender and race. More to the point, however, eliciting the prognosis in the form of the subjective probability density function more closely approximates reality and is less biased. The physicians' initial underlying expectation is the most accurate; it is as they move away from it through various processes that the prediction deviates more and more from the true outcome.

Clarifying the processes by which physicians formulate and communicate prognoses is important because physician prognostication has important downstream effects that are of central interest to health economics. Predictions of patients' survival affects the choice of medical therapy, the quality of patient care, and all associated medical resource utilization and costs. Prognosis becomes especially important when it comes to end-of-life care, when physicians make decisions regarding whether to continue curative medical treatment or to refer patients for hospice care (e.g., Christakis and Sachs, 1996; Campbell et al., 2004). For example, an over-prediction of patient survival directly increases the predilection to administer chemotherapy and decreases the probability of hospice referral, thereby increasing the cost of medical care for cancer. Prognosis also informs patients' economic behavior, including savings and consumption choices that play a major role in broader economic understanding of the life-cycle and public finance of aging (e.g., Gan et al., 2004).

An equally important concern is how different incentives in the US health care system affect physicians' ability to accurately assess their patients' survival and communicate it to their patients. The threat of malpractice in particular represents an important set of incentives that shapes physicians' diagnoses. The literature in this area suggests that physicians have an asymmetric loss function, as doctors face large losses if they fail to conduct a diagnostic test, while in contrast they do not seem to incur much cost from doing too many diagnostic tests. The growth of managed care in the US and tort law would seem to have also served to reshape the incentives physicians face when making their patients' prognosis (see Danzon, 1991, 1994; Reynolds et al., 1987). Better understanding of whether physicians exhibit biases in prognostication can contribute to the debate on the relative impact of defensive medicine on the nature of medical practice and on the costs associated with it (e.g., Newhouse, 1993; Kessler and McClellan, 1996).

One would expect that doctors should not have had any expectation that the patients in the sample we studied here would survive, since, after all, they were being referred to hospice and were seriously ill and close to death. If anything, however, we take this to be a situation in which the motivations (conscious, that is) to optimism or pessimism should be the least. Surely, when a doctor is faced with a patient of their own, who is within a few weeks of death, and who has agreed to go to hospice, this should be one of the 'easiest' clinical circumstance in which to formulate and communicate a prognosis, perhaps even formulate one with the least possible bias. Hence, if, even in this circumstance, our analysis identifies physicians' tendency to over-predict (or under-predict) their patients' survival, then this would be substantial evidence for what we take to be the intrinsic loss function of doctors. It is possible that any existing asymmetry of the loss would be amplified in patients who were newly diagnosed with cancer and who had years to live, but that is an empirical question about which we have no data.

Our results suggest that further research could explore a range of both economic incentives and economic consequences associated with the physician bias. Our study findings can be used to propose a new empirically testable hypothesis that prognostic bias may contribute to inflating medical expenses, especially for vulnerable populations such as Medicare recipients at the end of their lives. For example, recent evidence from Medicare claims suggests that hospice referral may result in as much as a 7% decrease in end-of-life Medicare expenses for cancer patients in the US (Campbell et al., 2004), suggesting real economic consequences of the physician decision-making process behind hospice referral. Also, the estimate that Medicare spends more than a quarter of its annual budget on care of patients in their last year of life (Hogan et al., 2000) suggests that further research aimed at understanding the tendency of physicians to overestimate patient survival could contribute to better allocation of resources, as well as better quality of care.

Appendix A. Asymmetric loss functions

In this, we introduce different loss functions, which allow us to analyze both the degree of asymmetry in physicians' forecast loss and the determinants of this asymmetry. We will set out the methodology for estimating both the average physician loss function and a loss function parameter for each individual in our data set. We estimate the average function because we are interested in generalizing the behavior of a representative physician. But in addition, we estimate individual bias parameters for two reasons. First, we recognize that physicians as a group are characterized by a great amount of heterogeneity in many aspects; it is reasonable to expect that psychological biases will also be distributed unevenly in the physician population. Second, we are interested in inference, investigating what factors affect individual physicians' degree of upward bias. To perform such inference, we need to "back out" an asymmetry parameter for each subject, and estimate a multivariate regression model that contains a set of factors hypothesized to influence the upward bias.

The standard rational expectations framework usually assumes that expert forecasters have a mean squared error (MSE) loss function. We can define the forecast error as $e_t = y_i - \hat{y}_i$, where y_t is the observed outcome and $\hat{y}_t$ is the forecasted or predicted value. (The subscript i identifies the decision-maker making the forecast, and the subscript t signifies the time the forecast is made.) The MSE loss function then takes the form:

$$L_{\mathrm{MSE}}(e_t) = ae_t^2, \tag{16}$$

where $a > 0$ is a constant. This functional form has proven useful because, under MSE loss, forecast errors have been shown to have mean zero and to be uncorrelated with other variables in the forecasters' information set. In finance and macroeconomics, a large body of research has used surveys of professional forecasters to test this form of rationality in forecasts (e.g., Fama, 1975; Zarnowitz, 1985; Zarnowitz and Lambros, 1987; Zarnowitz and Braun, 1993; Keane and Runkle, 1990, 1995; Bonham and Cohen, 1995; Mankiw et al., 2003). In addition to empirical results that challenge the assumption of loss symmetry, there have emerged a number of theoretical objections to assuming that economic agents making forecasts have a symmetric loss function, instead arguing that forecasting should be studied from a decision-making perspective that takes into account economic incentives that forecasters face (Christoffersen and Diebold, 1997; Christoffersen, 1998; Diebold et al., 1998; Diebold, 2001; Granger and Newbold, 1986; Granger and Pesaran, 2000; Pesaran and Skouras, 2001; Skouras, 2007; West et al., 1993).

While the earliest objection to the symmetric loss function in economics has been traced to Arrow and his colleagues' study of inventory and production (Arrow, 1958), the first commonly used asymmetric loss functions, including the quad–quad loss function, the lin–lin loss function, and the LINEX loss function, appeared subsequently. The quad–quad loss function simply modifies the MSE loss by assuming that the scaling constants are different on the positive and on the negative side of the loss (e.g., Elliott and Timmermann, 2002):

$$L_{\text{quad-quad}}(e_t) = [a + b \times 1(e_t < 0)] \times e_t^2. \tag{17}$$

Granger's (1969) lin–lin loss function takes a very similar form, but instead of a squared error, it uses the absolute value of the error:

$$L_{\text{lin-lin}}(e_t) = [a + b \times 1(e_t < 0)] \times |e_t|. \tag{18}$$

The third commonly used loss function is Varian's (1974) LINEX loss function, further studied by Zellner (1986). The LINEX, or linear-exponential, loss function allows loss on one side to rise approximately exponentially, while the loss on the opposite side rises linearly as the forecaster moves from the correct prediction. As discussed in introduction, Varian (1974) motivated his model by the observation that, in the real-estate market, the economic costs of over-assessment of property are much steeper than under-assessment, due to potential costs of appeals and litigation. The LINEX function takes the form:

$$L_{\text{LINEX}}(e_t) = b\ \exp(ae_t) - ce_t - b, \tag{19}$$

where $b > 0$, and a, $c \neq 0$. Assuming that $ab = c$, which ensures that the minimum of the $L_{\text{LINEX}}\ (e_t)$ is at $e_t = 0$ (Zellner, 1986), the LINEX loss function is then:

$$L_{\text{LINEX}}(e_t) = b[\exp(ae_t) - ae_t - 1], \tag{20}$$

where $b > 0$, and $a \neq 0$.

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