Review of Economic Studies (2013) **80**, 949–983 doi:10.1093/restud/rds046

Advance access publication 7 January 2013

Overconfidence and Social Signalling

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First version received March 2011*; final version accepted September* 2012 (*Eds.*)

Evidence from both psychology and economics indicates that individuals give statements that appear to overestimate their ability compared to that of others. We test three theories that predict such relative overconfidence. The first theory argues that overconfidence can be generated by Bayesian updating from a common prior and truthful statements if individuals do not know their true type. The second theory suggests that self-image concerns asymmetrically affect the choice to receive new information about one's abilities, and this asymmetry can produce overconfidence. The third theory is that overconfidence is induced by the desire to send positive signals to others about one's own skill; this suggests either a bias in judgement, strategic lying, or both. We formulate this theory precisely. Using a large data set of relative ability judgements about two cognitive tests, we reject the restrictions imposed by the Bayesian model and also reject a key prediction of the self-image models that individuals with optimistic beliefs will be less likely to search for further information about their skill because this information might shatter their self-image. We provide evidence that personality traits strongly affect relative ability judgements in a pattern that is consistent with the third theory of social signalling. Our results together suggest that overconfidence in statements is more likely to be induced by social concerns than by either of the other two factors.

Key words: Confidence, Bayesian updating, Personality traits

JEL Code: D03

1. INTRODUCTION

Good economic decisions require a well-calibrated belief about one's ability. Instead, evidence from psychology and economics suggests that individuals may have excessive confidence in their abilities. This excessive confidence may be absolute (i.e. subjects predict that they will perform better than they really do) or relative (subjects predict that their performance ranks higher compared to that of others, than it really does). In this article we will use the term overconfidence to describe the relative version of excessive confidence.[1] In a typical study few individuals place themselves in the bottom 40% of a relative skill distribution, largely independent of the skill in question (Alicke *et al*., 1995; Dunning, 1989; Svenson, 1981). These beliefs have consequences: other studies link measures of overconfidence to behaviour, and show that more confident judgements are associated with more daring behaviours. For example, Malmendier and Tate (2008) show that more confident CEOs make more daring merger decisions (Malmendier and Tate, 2005). Barber and Odean (2001) show that men engage in more frequent trading in common stock. This trading reduces their returns substantially relative to women. Thus, if overconfidence is truly a judgement bias, these studies should raise concern, as they raise the possibility that individuals systematically make suboptimal decisions because they choose based on biased beliefs.[2]

Although overconfidence and its effects have been widely studied, the cognitive and psychological mechanisms generating overconfident judgements are not well-understood. In this article, we provide a test of three different theories providing an explanation of observed overconfidence. The data we use were collected from a large sample ($N = 1068$) of trainee truck drivers at a driver training facility of a large U.S. company. The subjects participated among others in two tests of cognitive ability in which appropriate monetary incentives were provided. The first test was part of a standard non-verbal IQ test, Ravens Progressive Matrices (Raven, 2000), which involves identifying an underlying pattern in a set of visual cues. The second was a section of the Adult Test of Quantitative Literacy (hereafter called Numeracy), from the Educational Testing Service (ETS), which involves reading text samples and solving arithmetic problems that are based on the text.

The first question we address is whether overconfidence should be viewed as a systematic bias in judging one's ability, or whether there is some natural way in which rational agents could appear overconfident. If individuals have perfect knowledge of their abilities, a result showing that 50% of the individuals rate themselves in the top 25% of an ability distribution necessarily implies a judgement bias of some sort.[3] However, assuming perfect knowledge of one's ability may not be realistic. Rather, individuals may only vaguely know their abilities, and update their beliefs as new information arrives. Benoît and Dubra (2011) show that, if individuals have imperfect knowledge of their own ability, even individuals performing correct Bayesian updating starting from a common prior may report what seems to be an overconfident belief. They point out that, in most studies, individuals are asked to indicate their most likely place in the ability distribution, and provide a general characterization of the information structure leading to results such as, for example, 50% of the individuals rationally putting themselves in the top 25% of the ability distribution. Intuitively, this can arise if the signals individuals receive become noisier the better the signal values are, akin to taking an easy test. Everyone who fails the test can be sure that his ability is low; however, low-ability types sometimes also pass the test by sheer luck. But still, passing the test rationally leads individuals to believe it is more likely that they have high

1. Individuals might err in either the direction of over or underconfidence, but overconfidence seems the dominant behaviour, although individuals may be underconfident in specific conditions, for example when the task is hard (Hoelzl and Rustichini, 2005).

2. A slightly different meaning of the word is in the literature reviewed in Hoffrage (2004). In this line of research, confidence describes the subjective probability that the individual assigns to the event that his answer is correct.

3. Merkle and Weber (2007) do show overconfidence leads to bias in beliefs. Their test is based on eliciting the c.d.f. of beliefs over abilities for which it is difficult to pin down the true distribution. This allows them to reject Bayesian updating without even knowing what the true distribution of ability is.

ability, therefore creating 'overconfidence' by this measure.[4] To bolster this result, they also provide an experimental test of overconfidence. Benoît and Dubra (2011) show that what seems to be evidence of overconfidence may be consistent with unbiased Bayesian updating. We call the hypothesis that judgements on relative positions of individuals are produced by Bayesian updating (from a common prior) and truthful revelation of the posterior, or some statistics of it, the *Bayesian hypothesis*.

However, we show in this article that if judgements are the result of Bayesian information processing from a common prior, then testable restrictions are placed on the joint distribution of beliefs and individual's true ability. In particular it must be true that of all individuals placing themselves in ability quantile k, the largest (modal) share of them must actually be from quantile k. Therefore, we can base a test of the Bayesian hypothesis on whether this is the case. We test the model with a large sample of ability judgements and we clearly reject the restriction: in general, individuals from an ability quantile $j<k$ are more likely to think they are in quantile k. Our test is general in the sense that it rejects *any* model that relies on Bayesian updating to form overconfident relative ability judgements, independently of the motives behind the formation of the judgements. This test thus rejects the joint hypothesis of Bayesian updating, the common prior assumption, and truth-telling, leaving unanswered these questions: which part of the joint hypothesis has failed, and which theory can explain our data?

The theoretical literature on self-confidence assumes that individuals have reason to hold correct beliefs, since this knowledge helps them choose actions, but other factors may motivate individuals to hold overly optimistic beliefs. This literature proposes three broad reasons for the existence of optimistic rather than realistic self-assessment (Bénabou and Tirole, 2002): consumption value (individuals like to have positive self-image as a good in itself), motivation value (optimistic assessments may induce higher second-stage effort, and hence better outcomes, than correct ones), and signalling value (positive self-confidence makes a positive external representation of oneself easier). The first two reasons motivate an individual to have self-image concerns independently of his social relations. A way in which optimistic beliefs are produced in models of image concerns is described, for example, in Kőszegi (2006); Weinberg (2006). In these models, individuals like to believe that they have high ability, but their beliefs are constrained by Bayesian updating. This endogenously generates an "easy-test" information structure akin to Benoît and Dubra (2011) that depends on the individual's beliefs: once individuals are sufficiently certain that they are of high ability, they stop seeking information, as this only offers the risk of revising their beliefs downward by error. In contrast, individuals with a low self-assessment of their relative ability seek information as long as there is a chance for improvement. This mechanism generates overconfident beliefs.

We test the central mechanism that generates overconfident beliefs in these models by offering our subjects the opportunity to find out how well they did in the tests relative to the other participants. Our data strongly reject an important prediction of self-image models: we find that individuals with high beliefs are uniformly *more likely* to demand information about their ability. Thus, although beliefs do play an important role in demanding information, they do not in a way consistent with preserving self-image generating overconfidence by themselves.

The social signalling interpretation of overconfidence given in Bénabou and Tirole (2002) focuses on a different aspect: the idea that the easiest and most effective way to lie is to lie to yourself first. This moves back in the direction of a bias in judgement, but a bias with social roots rather than individual ones, and could offer a functional explanation for the existence

4. Although overconfidence in this measure may prevail in the population, the beliefs are still unbiased, as the individuals who think they are in the upper half of the distribution recognize that this is not guaranteed and, in their implicit internal model, attach the correct probability to this state.

of a preference for high self-confidence. Of course, social signalling may also have a more direct and strategic interpretation: subjects called upon to provide a self-evaluation may consider this as a social act, with possible social consequences, and may consciously choose to report a higher estimate of their own abilities than they actually hold. We formulate this hypothesis as a simple model, give a more precise definition of social signalling, and discuss its implications and predictions in Section 6.

Our data allow a sharp separation between theories (such as those in Kőszegi, 2006; Weinberg, 2006) which appeal to consumption and self-motivation value on the one hand, and the explanation provided by social signalling on the other. We focus on this contrast. Our results are consistent with a model in which individuals enjoy acquiring evidence confirming a positive belief, and enjoy sending public signals based on such evidence, rather than preserving a fortuitous positive self-image. We further corroborate this interpretation by examining how individual personality differences affect relative ability judgements (see Biais *et al*., 2005, for an earlier study of the implication of personality traits on overconfidence). We measure traits of individuals with their answers to the Multidimensional Personality Questionnaire (MPQ), an eleven scales personality test. Consistent with our theory, we find that more socially dominant individuals (that is individuals with a high score in the Social Potency scale of the MPQ) make more confident judgements, holding constant their actual ability. This effect is also quantitatively large: of those individuals with a below-median score in social dominance, 33% think they are in the top 20% of the IQ distribution. Of the individuals with an above-median score in social dominance, 55% think they are in the top 20%, when, in fact, 20% of both groups are in the top 20%. These results are robust to the inclusion of a large set of controls, and are highly specific to the personality trait predicted by our theory. Similarly, the specific trait of aversion towards negative social feedback (the stress-reaction scale), reduces overconfident judgements, holding actual ability constant. These same personality traits also predict which individuals revise their judgements after having taken the test. This suggests that one of the mechanisms behind overconfidence is socially motivated, biased interpretation of information.

In summary, our results show that overconfidence cannot arise from Bayesian updating on signals about one's ability. Our results also lend little support to the view that overconfidence is the result of indirect self-deception through the management of information acquisition, as we find that individuals with optimistic beliefs about themselves seek more information, in contradiction to those models. Instead our findings suggest that overconfidence is likely to arise in the process of communicating judgements about one's relative performance to others.

The remainder of this article is structured as follows: Section 2 describes our empirical setup. Section 3 presents the basic findings on overconfident relative ability judgements. Section 4 introduces a framework of incomplete information about one's own ability, derives restrictions that this places on relative ability judgements, and tests them. Section 5 discusses image preservation as a source of overconfidence, and provides an empirical test. Section 6 presents a simple model of social signalling and evidence on how personality traits that proxy one's concern for the opinion of others are related to overconfidence. Section 7 concludes.

2. DESIGN OF THE STUDY

The data for this study were collected from 1068 trainee truck drivers at a driver training facility on Saturdays that fell in the middle of a 2-week basic training course the subjects were undertaking to earn a commercial driver's license. The two tests were part of a larger data collection process for the Truckers and Turnover Project (Burks *et al*., 2009), which was administered to participants in groups of 20–30 from December 2005 to August 2006. At the beginning of each session, subjects were guided through a consent form that explained all the conditions for participation in the study. A central point in the informed-consent process was to explain to the participants that their employer would see none of the individual data collected in the project (see Burks *et al.*, 2008, for more details).

The sequence of events was the same in both tests. First, using the standard instructions that came with each test, the nature of the test was explained, directions about how to complete questions were given, and a sample question was provided and the correct solution presented. After the instructions, we recorded the first self-assessment of the subjects' abilities: the subjects were asked how well they thought they would do in this test relative to the rest of the session's participants by identifying the quintile of group performance in which their score would fall. After the test was completed, the subjects were asked to self-assess a second time by again picking the quintile of group performance in which their own score would fall.

We paid subjects for their attendance and their performance (Borghans *et al.*, 2008). Each subject took part in two sessions, each 2-h long; both cognitive skills tests were in the second session. We paid an initial amount of $20 for participation at the beginning of each session. In addition, for each cognitive skill test, we randomly selected two subjects from each group after the test and paid each of these persons $1 for every correct answer in the IQ test (maximum possible payout of $48), and $2 for every correct answer in the Numeracy test (maximum possible payout of $24). We also paid each subject $2 each time the subject correctly identified the quintile into which his or her own score actually fell (maximum possible payout of $4 per test). Payments depending on performance were explained before each test, as part of the test's instructions. Virtually all of the driver trainees participated in our study.

Because the payout calculations for the Numeracy task were manual, and because subjects were enrolled in a course that continued for another week, we paid out all the earnings from participation beyond the show-up fees at the beginning of the work week following the Saturday test administration. This provided us with the opportunity to also ask subjects, immediately after their second self-assessment response on each test, whether they would like to learn on payout day both their exact score, and what their actual relative performance was, that is which quintile they were actually in. Those who answered "no" only received their payout, and not this extra information. Thus, this answer is our measure of each subject's demand for information about their relative performance: "yes" signalled the desire to know. We added this question after data collection began, so there are 839 subjects that indicated their demand for information on the IQ test, and 889 that did so on the Numeracy test.

In addition to providing a clear measure of the demand for information about one's relative performance, this design provides incentives to truthfully report one's self-assessment of relative performance, and to make that estimate as accurate as possible. A strength of the design is that we asked subjects about their performance relative to a specific group of people, whom they had known for more than a week by the time of the experiment. Therefore, unlike the most common studies of overconfidence in the psychology literature, our design rules out that subjects were comparing themselves to groups outside the lab. Finally, it avoids the ambiguities of earlier studies that asked individuals whether they were above or below the mean.[5] During the entire experiment we collected a variety of additional demographic and socio-economic information.

Subjects also filled out the MPQ. The *MPQ* is a standard personality profile test (Tellegen and Waller, 1994; Tellegen, 1988; Patrick *et al.*, 2002). It consists of questions concerning 11 different scales that represent primary trait dimensions: wellbeing, social potency, achievement, social closeness, stress reaction, alienation, aggression, control, harm avoidance, traditionalism, and absorption. In our study we used the short version (Patrick *et al.*, 2002), which

5. If, *e.g.,* the median of abilities is significantly above the mean, a fraction significantly larger than half could correctly answer that they are better than average, which makes the interpretation of these studies difficult.

has 154 multiple choice questions. The MPQ is a widely used questionnaire that aims at measuring stable differences in individual personality (see Tellegen and Waller, 1994, for a discussion of its methodology of deriving the scales). The MPQ is a well-validated scale, and predicts a whole array of behaviours with the theoretically expected correlations, ranging from mental disorders (Krueger *et al*., 1996; Krueger, 1999), crime (Krueger *et al*., 1994), and gambling (Slutske *et al*., 2005).

3. EVIDENCE OF OVERCONFIDENCE

Table 1 presents some basic descriptive statistics. The first panel in the table shows the number of correct answers in the two cognitive tests. Burks *et al*. (2008) show that the distribution of the score in the Raven's task in our sample is close to that of representative samples, although slightly lower: for example, the median score in our sample is 47.5, in the representative sample (reported in Raven, 2000, the median is 52). Turning to the demographics of our sample, we see that the most frequent education level in our sample is a high school degree, though some have also degrees from technical schools, and a significant fraction has at least some college education. The table shows that our sample is predominantly Caucasian, male, and were on average in their late thirties. See Burks *et al*. (2008, 2009) for a more extensive discussion.

TABLE 1
Descriptive statistics

Test scores: number of correct answers.

	Mean	Standard deviation	Min	Max
Numeracy test	8.42	2.62	0	12
IQ test	45.34	8.13	1	60
Education: highest level attained				
Middle school	4.21%			
High school	38.90%			
Technical school	14.3%			
Some college	34.4%			
College	5.8%			
Graduate school	2.2%			
Ethnic categories				
Caucasian	82.7%			
African-American	14.2%			
Indian	2.9%			
Asian	0.9%			
Latino	2.6%			
Other	1.6%			
Other demographics				
Age	37.43	10.90	21	69
Male	89.5%			
Household Income (in thousands of US Dollars)	53.04	27.02	10	150

Notes: N = 1068 individuals.

3.1. *Overconfidence in relative ability judgments*

In this subsection, we present the basic evidence on overconfidence in our study. This serves two purposes: to show that our results are comparable to overconfident judgements found in other studies, and, to motivate the theoretical model we discuss later.

Figure 1 displays the distribution of relative ability judgements across all individuals. It shows a typical pattern found in a large number of studies: very few individuals rate their ability in the bottom 40% of the ability distribution. In contrast, well above 60% think they are in the top 40%. The figure shows a very similar pattern for the relative ability judgements in the two tests.

Figure 2 displays relative ability judgements as a function of the true ability in the IQ test, reporting under- and overconfident judgement relative to the true ability of the individual. On the horizontal axis we report the quintile of the real performance of the subject, and on the vertical axis, for each quintile, we report the percentage of subjects who predict that their performance is going to be higher than what really was (dark grey bars) and the percentage of subjects who predict that their performance was going to lower (light grey lines). Shades of colour indicate the extent of overconfidence: light shading indicates that the individual is just one quintile off, darker shading indicates that the individual is more than one quintile off. Panel A displays relative ability judgements before the IQ test. The figure shows that overconfident judgements are pervasive across the ability spectrum, except where impossible by definition in the top ability quintile. The figure also shows that the relative ability judgements are strongly asymmetric: underconfidence is much rarer than overconfidence. Panel B in Figure 2 displays relative ability judgements after the IQ test and shows essentially the same pattern: taking the test does not qualitatively change the distribution of beliefs compared to those reported earlier, after just the instructions and practice

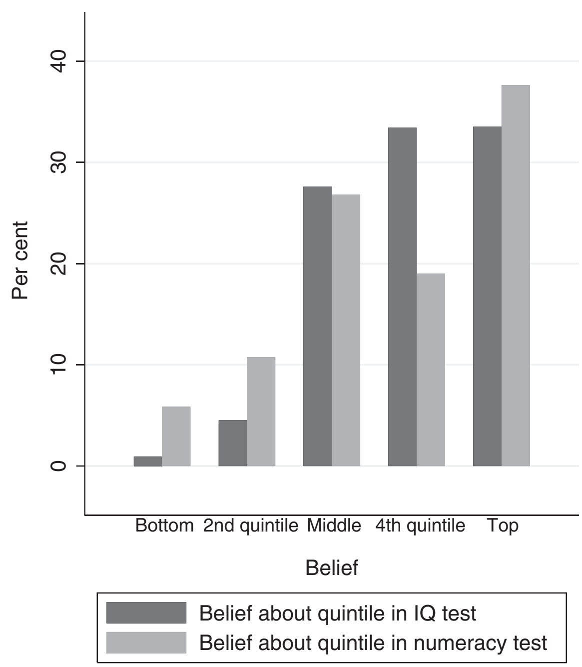

FIGURE 1

Distribution of beliefs about ability in IQ test and Numeracy test

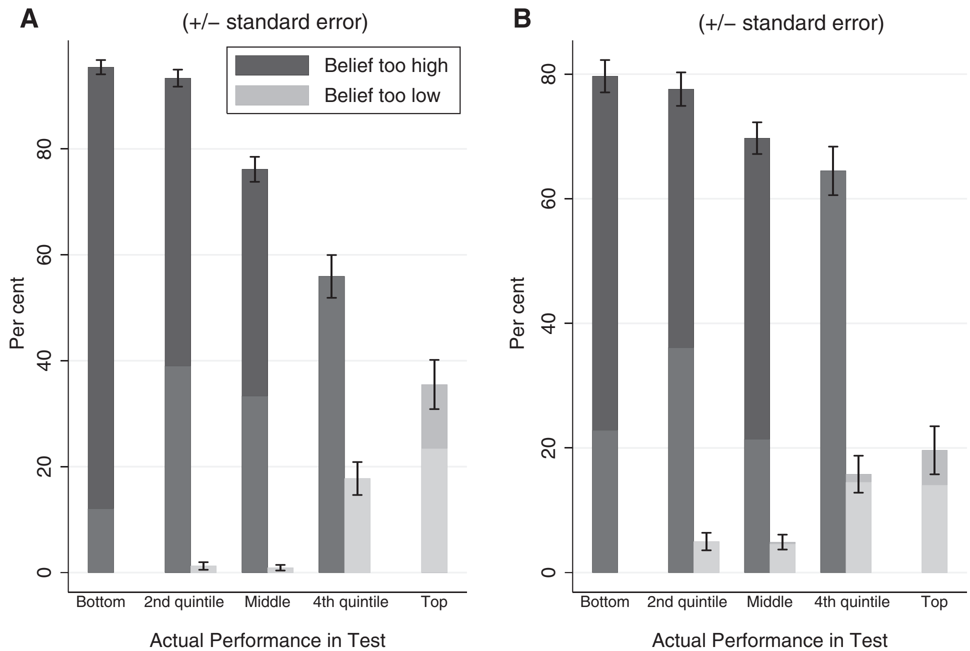

FIGURE 2

Relative performance judgements as a function of actual ability: IQ. On the horizontal axis we report the quintile of the real performance of the subject. On the vertical axis, for each quintile, we report the percentage of subjects who predict that their performance is going to be higher than what really was (dark grey bars) and the percentage of subjects who predict that their performance was going to lower (light grey lines). The shades of colour indicate the number of quintile in the error. Light colour indicates only one quintile off; a darker colour indicates two or more quintiles off. (A) Beliefs prior to IQ test; (B) beliefs after IQ test

question. The relative ability judgements for the Numeracy test are presented in Figure 3: the results are very similar to the case of IQ test.

4. THE BAYESIAN MODEL OF OVERCONFIDENCE

In this section we establish the benchmark model of the behaviour for a population that is forming beliefs about their own ranking using belief updating based on the information they have available (as in Benoît and Dubra, 2011). We discuss their result that such a model can produce features of the relative ability judgements that we showed in the previous section. We then derive new testable restrictions imposed by the Bayesian theory.

In the model we consider a large population of individuals, each one endowed with a type t, which is the value of a specific characteristic. For example the type of an individual might be his height, something easily determined and observed. Another more interesting example is his ability to score high on an intelligence test, a quality that we briefly described as the individual's IQ. We are interested in types that are ordinal quantities. In what follows, we will restrict attention to judgements about the individual's position in the distribution of outcomes. As in our empirical study we elicit judgements about the quintiles, so we also restrict our notation in the model to quintiles.

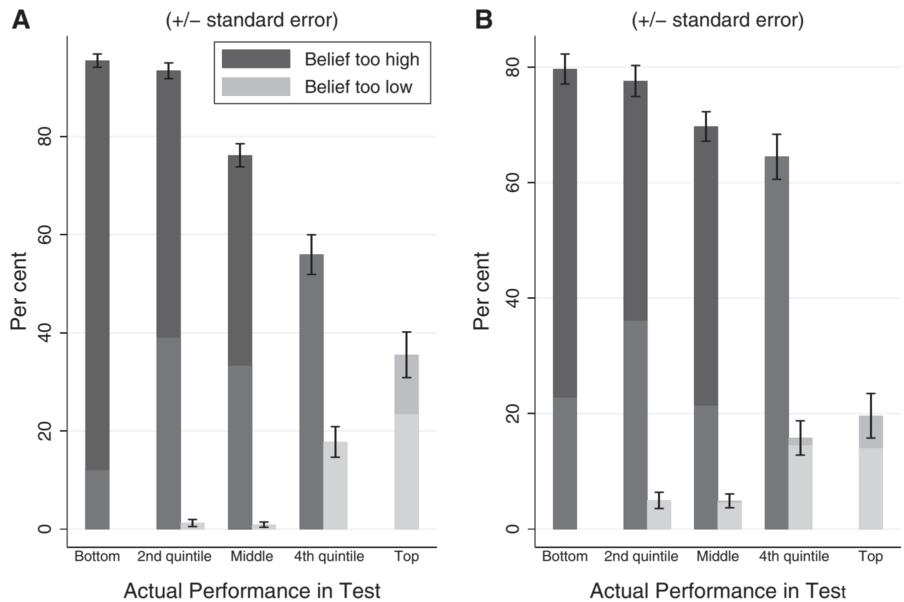

FIGURE 3

Relative performance judgements as a function of actual ability: Numeracy. See Figure 2 for explanation. (A) Beliefs prior to Numeracy test; (B) beliefs after Numeracy test

The type of each individual is determined independently, according to a known probability measure on the set of types. Thus, the population has a common prior on the distribution of types, which, since we define types are percentiles, is the uniform distribution. Individuals do not know their type, but during their life they gather information by observing private signals about it. On the basis of this information they update in a Bayesian fashion their belief about their type, which initially was the common prior, and therefore also they update the belief they have about their own relative position in the population with respect to the characteristic we are considering. For example, through their school performance, job performance, as well as occasional exchanges with other people they form an opinion about their IQ, and hence of their relative standing with respect to this characteristic within the population. Formally, we assume that individuals observe an outcome $x_i \in X, i=1,...n$ from some signal space X, where we assume n is larger than 5, the number of quintiles.[6] A subject participating in an experiment like ours comes to the laboratory with this posterior belief about his ability. Denote the probability that an individual receives signal x_i given that he is of ability t_k by $p_k(x_i)$. Then the individual's posterior beliefs about his ability is given by

$$\Pr(t_k|x_i) = \frac{p_k(x_i)}{\sum_j p_j(x_i)}. \tag{1}$$

The signal structure $p=(p_k(x_i))_{k=1,...,5,i=1,...,n}$ is the true information structure. We have very little hope of determining this object empirically in a direct way. So suppose we ask the

6. Notice that we restrict attention to one draw from a signal structure, rather than, *e.g.*, a dynamic acquisition of signals. Dynamic acquisition signals can be redefined as a single draw from a single signal structure.

individual to predict the quintile in which his IQ score will fall, and promise him a payment if his prediction is correct. Let us assume that our incentives are sufficient motivation for him to state the truth, and that he believes that our test is unbiased. Then an individual who observes the signal x_i will pick the most likely quintile given x_i, that is the individual will indicate that he is *most likely* in ability quintile $s(i)$, where

$$s(i)=\arg\max_j Pr(t_j|x_i)=\arg\max_j p_j(x_i). \tag{2}$$

We call the theory that subjects follow this procedure of deriving posterior beliefs with Bayesian updating from a common prior and then truthfully report to us the most likely quintile the *Bayesian model*. A large fraction of subjects thinking that they are in the top two quintiles is consistent with this model. To illustrate, consider an example (very close to the one presented in Benoît and Dubra, 2011) with only two types, good and bad. In the top two quintiles (40%) we find good types, and the remaining three quintiles are bad types. This is the distribution of types and the common prior. The only source of information for individuals is a test that everybody takes. Good types pass the test for sure, bad types only pass it with probability 50%. The posterior probability that an individual is a good type if he passes the test is

$$\Pr(\text{good type}|pass)=\frac{1\cdot 0.4}{1\cdot 0.4+0.5\cdot 0.6}=\frac{4}{7}, \tag{3}$$

so individuals who pass the test and answering truthfully state that their most likely type is the good type. A fraction of 70% of the population passes the test (all the good types, plus half the bad types): Thus in this population, 70% truthfully and correctly report that they most likely belong to the top 40%, much as we observe in the data presented in the previous section. Beliefs are on average correct: 70% of the population believe that they are good with probability 4/7, and 30% believe that they are good with probability 0. Overconfidence in beliefs arises because the test was easy (all good types and half of the bad types pass the test). If the test was hard (e.g., all bad types and half of the good fail), underconfidence would arise, and only 20% would state that they are good types.

4.1. *Testable restrictions on beliefs*

Incomplete information about one's abilities, and a particular feature of the signal structure (an easy test) may lead to overconfident beliefs. However, the Bayesian model imposes testable implications on how the distribution of relative ability judgements should be related to true abilities. These are testable because the experimenter also observes the true score of the individual in the test, so he has at the end of the experiment for each subject a pair of observations, (*true score, stated quintile)*. The true score is not a precise measure of the IQ of an individual, of course, but it is good enough so that we can ignore sampling error with respect to the quintiles.

Since individuals have an incentive to choose the most likely quintile, the Bayesian model requires them to use (1) to form their posterior and to select their statement according to (2). Denote the expected fraction of individuals in true ability quintile k assigning themselves to quintile j based on the signal structure provided in (1) by $q_k(s_j)$. We call the function $(q_k(s_j)_{k,j=1,\dots,5})$ allocating each type k to five quintiles in specific proportions, the theoretical allocation function. It defines a 5×5 matrix of relative ability judgements. Note that for every true ability quintile k, $\sum_j q_k(s_j)=1$. The items in the diagonal denote the fraction that hold the correct beliefs about their abilities. Entries $q_k(s_j)$ with $k<j$ indicate individuals who hold overconfident beliefs, whereas entries with $k>j$ indicate the fraction of individuals holding underconfident beliefs.

What restrictions does Bayesian updating place on this matrix? Because individuals pick the most likely quintile given the signal x_i that they received, the largest (modal) group of individuals thinking they are in quintile k must belong to that ability quintile. That is, Bayesian updating imposes that:

$$q_k(s_k) = \max_l q_l(s_k). \tag{4}$$

In the Appendix, we characterize this property more fully. The theoretical allocation function allows us to sidestep a problem that has no empirically identifiable solution: what is the true information structure p? If the behaviour we want to describe only depends on the posterior distribution over quintiles given the signal, then we may assume that the true information structure takes values in the simple signal space given by the set of quintiles. To see this, consider an information structure where individuals observe some signal x in some arbitrary signal space X, compute the posterior on their type, and state the most likely quintile. This information structure, in our environment in which the only task of the individuals is to state the most likely quintile, is equivalent to a simple information structure where individuals are directly communicated the quintile they should state (so the signal space is the set of quintiles), and they do so (because the diagonal condition (4) insures this behaviour is incentive compatible). The theoretical allocation function derived from equations (1) and (2) can be considered a canonical information structure. The harder problem: "Is there an information structure that can generate the data?" has been replaced by the easier problem: "Is there a canonical information structure that can generate the data?" This problem has an answer, that we present in the next section.[7]

4.2. *Rejection of the Bayesian model*

We have seen that Bayesian updating implies condition (4), which we may call the diagonal condition, because if the theoretical allocation function is read as a matrix, then the entries with the largest values are on the diagonal. But how can restrictions imposed by (4) be tested against the *empirical allocation function* $\hat{q}_k(s_j)$, that is, the empirical distribution of relative performance judgements as a function of the individuals' true ability? Intuitively, strong evidence that the main diagonal condition is violated rejects the Bayesian model.

Table 2 displays the empirical allocation function for the Numeracy and IQ test. The table shows that in both cases, the empirical frequencies violate the diagonal condition. For example, in the Numeracy test, only 18% of the individuals from the third quintile put themselves into the third quintile. In contrast, 40% from the first quintile and 27% from the second quintile put themselves in the third quintile, in violation of the diagonal condition (4). But is the violation significant? Since we do not know the underlying signal structure, how likely is it that a signal structure satisfying (4) generated the data in Table 2? We propose a test that gives the Bayesian model the best chance not to be rejected.

We estimate the parameters of the theoretical signal structure by maximum-likelihood subject to the constraint imposed by (4). That is, we compute the $q = (q_k(s_j))_{k,j}$ that solves:

$$\max_q \sum_{j,k} n_{kj} \log(q_k(s_j)), \tag{5}$$

7. Notice that we have so far assumed that all individuals draw signals from a common signal structure. This, however, is not a crucial assumption. If different individuals drew signals from different signal structures, this can be modelled as a meta signal structure, in which individuals first observe from which sub-structure they will draw signals.

TABLE 2
The empirical allocation functions $\hat{q}_k(s_j)$

	Numeracy test					IQ test				
	s_1	s_2	s_3	s_4	s_5	s_1	s_2	s_3	s_4	s_5
t_5	0.0	0.0	0.1	0.27	**0.62**	0.004	0.016	0.121	0.271	**0.579**
t_4	0.004	0.009	0.091	**0.298**	0.59	0.0	0.014	0.168	**0.355**	0.461
t_3	0.0	0.0125	**0.181**	0.362	0.443	0.006	0.031	**0.262**	0.375	0.325
t_2	0.004	**0.0**	0.272	0.377	0.345	0.0	**0.04**	0.39	0.363	0.204
t_1	**0.02**	0.02	0.401	0.376	0.175	**0.033**	0.11	0.42	0.322	0.104

Notes: The empirical allocation function indicates for each ability quintile k, what fraction of individual put themselves in ability quintile j.

TABLE 3
Constrained maximum-likelihood estimators of the allocation function $q_k^{ML}(s_j)$

	Numeracy test					IQ test				
	s_1	s_2	s_3	s_4	s_5	s_1	s_2	s_3	s_4	s_5
t_5	0	0	0.121	0.232	**0.646**	0	0	0.101	0.277	**0.621**
t_4	0	0	0.159	**0.335**	0.504	0.004	0.008	0.080	**0.378**	0.528
t_3	0	0.007	**0.364**	0.275	0.352	0	0.01	**0.343**	0.290	0.355
t_2	0.012	**0.106**	0.364	0.335	0.180	0.004	**0.015**	0.269	0.373	0.337
t_1	**0.071**	0.106	0.364	0.335	0.122	**0.012**	0.015	0.343	0.378	0.251

Notes: The maximum-likelihood estimator is the solution of the problem described by equation (5). It indicates for each ability quintile k, what fraction of individual receives a signal that would induce him to choose the quintile j as most likely.

subject to for every $k, j, q_k(s_j) \geq 0, \sum q_k(s_j) = 1$ and

$$\text{for every } k, q_k(s_k) = \max_l q_l(s_k),$$

where n_{kj} is the number of individuals of ability quintile k saying that they are in quintile j. This is a concave problem and maximization is straightforward with numerical methods. Denote the solution to (5) by $q_k^{ML}(s_j)$. Notice that this gives the best chance to the null hypothesis of Bayesian updating, since we pick q^{ML} as the one satisfying (4) that best fits the observed data. The constrained maximum-likelihood estimator for Numeracy and IQ test are reported in Table 3. The table shows the balance the ML estimator has to strike between matching the data while at the same time respecting the diagonal condition, thus creating differences between the estimated and the empirical allocation function.

To quantify these differences, we calculate the fit of q^{ML} to $\hat{q}$ as the mean square root error from each cell:

$$\hat{d} = \frac{1}{25}\sqrt{\sum_{j,k}(\hat{q}_k(s_j) - q_k^{ML}(s_j))^2} \tag{6}$$

The distance measure is $\hat{d}^{IQ} = 0.026$ for the IQ test, and $\hat{d}^{Num} = 0.033$ for the Numeracy test. That is, the average deviation from the ML estimate of q is 2.6 percentage points in the IQ test and 3.3% points in the Numeracy test. In order to assess whether the fit $\hat{d}$ is improbably bad, we generate 100,000 simulations of the same sample size as our data using q^{ML} as the data generating mechanism and calculate the distances d_n for each trial n. This provides us with an empirical distribution function for the distance measure d to calculate the probability that a draw from q^{ML} has a worse fit than the empirical allocation function $\hat{q}$. The p-values are $p=0.005$ for the IQ test, and $p=0.001$ for the Numeracy test. Therefore, we clearly reject the hypothesis that our data are generated by the joint hypothesis of imperfect information about ability, Bayesian updating from a common prior using this information, and truthful revelation of the belief thus formed.

5. SELF-IMAGE CONCERNS AS THE SOURCE OF OVERCONFIDENCE

The previous section tests and rejects a wide class of models that rely on Bayesian updating from a prior after exogenous arrival of information. Other models have been developed to explain overconfidence arising endogenously as a function of individuals' choices. Two recent articles (Kőszegi, 2006; Weinberg, 2006) have argued that a concern for self-image can lead to overconfidence. If individuals' utility depends on their belief about their ability, this can lead to an endogenous mechanism that produces results as if they were drawing signals from the "easy-test" signal structure in Benoît and Dubra (2011). This, however, requires that utility is sufficiently "kinked" in the belief. Kőszegi (2006) provides an example in which an individual's utility discretely increases by some fixed amount v if the individual believes that the chance that his ability t is below some threshold $\hat{t}$ is small. Formally, utility is given by

$$U(c,\hat{t})=u(c)+v\cdot I(F(\hat{t})\leq x), \tag{7}$$

where $F()$ is the c.d.f. of the individual's current belief over his ability and $I()$ is the indicator function. To see how this can lead to overconfidence, assume that the individual's belief currently is that $F(\hat{t})<x$ and that he is offered more information about his ability. Suppose that the only change in utility he can have from further information is from the possible change in self-image. Then he will never seek more information, because more information only harbours the risk of revising his belief downward. Conversely, if $F(\hat{t})>x$, the individual will seek more information. If his belief is further revised downward, this leaves utility unchanged. If the individual receives a positive signal, he will gain utility v if $\tilde{F}(\hat{t})<x$ where $\tilde{F}()$ is the c.d.f of beliefs incorporating the new information. Notice that this logic continues: whenever an individual with belief $\Pr(t\leq\hat{t})>x$ is offered new information, he will seek it. Thus, this model can generate a pattern in which individuals with low beliefs will seek all the information they can find, whereas individuals with high beliefs will have less accurate information: of all the individuals with initially low beliefs, all those with high ability will revise their views upward. In contrast, some of the individuals who initially had high beliefs (i.e. $\Pr(t\leq\hat{t})\leq x$), will have received good signals by chance, but will not discover their mistake. The result is that too many individuals will believe they have high abilities.

5.1. *An empirical test: the demand for information*

We provide a direct test of the central mechanism of this class of models. We test the prediction that individuals with optimistic beliefs should be less likely to seek more information about their ability. Recall that after each test, we offered the subjects the opportunity to find out exactly how well they did relative to the others. We thus gave the individuals the chance to obtain more information, exactly as required in the model. This test also has the feature that it does not rely on the assumption of common priors. Rather, it measures the demand for information directly as a function of the individuals' beliefs.

Figure 4 displays the fraction of individuals demanding information about their performance as a function of how well they did in the test and their stated belief about their performance.

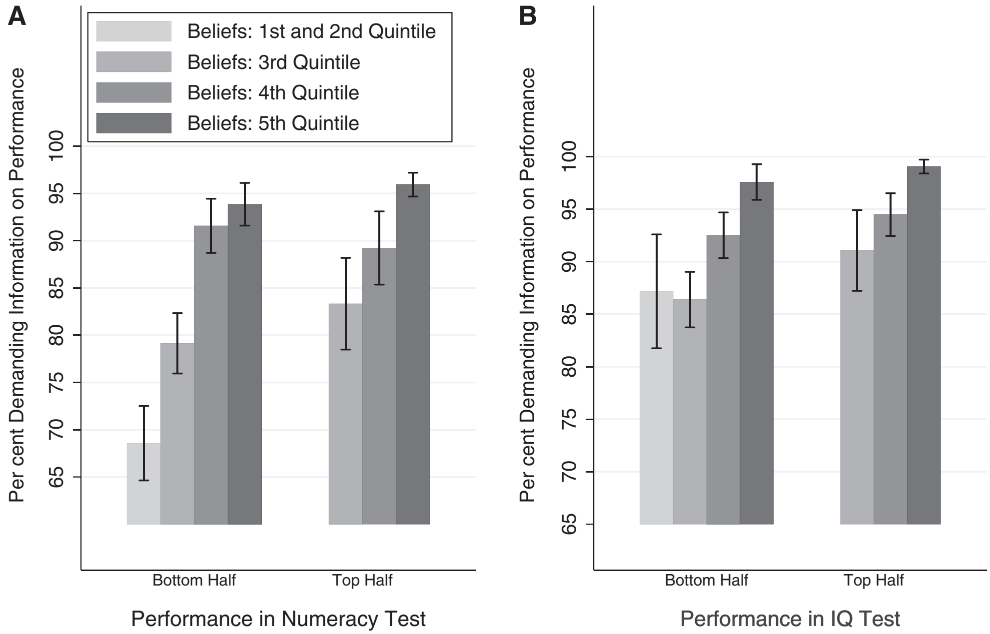

FIGURE 4

The demand for information. (A) Demand for information and beliefs about ability (Numeracy); (B) demand for information and beliefs about ability (IQ)

Notes: Caps indicate standard error of the mean.

Because of the small number of observations in the bottom two quintiles, we collapse them into one group. Panel A in Figure 4 displays the results for the IQ test, whereas the results for the Numeracy test are displayed in Panel B. The figure also controls in a rudimentary way for differences in true abilities by splitting the sample into the top and bottom half of the performers. Thus, by comparing individuals with identical beliefs in the top and bottom half of the true abilities, we can gauge the impact of true ability on the demand for information.

Both Panels show a strong impact of beliefs on the demand for information. However, individuals with more confident beliefs are more likely to ask for the performance information, in contrast to what is predicted by the models of self-image concerns discussed above. This tendency is monotonic across quintiles. In particular, the bottom two quintiles never display the highest propensity to seek information, as the theory predicts. In the case of either test, there is another quintile with substantially higher demand for information. Comparing across the panels for the top and bottom ability, the figure suggests that there is no strong relationship between ability and the demand for information.

To formally test the model, we estimate the following probit equation

$$\Pr(seek_i = 1 | q_i, x_i) = \Phi(\gamma q_i + \beta' x_i), \tag{8}$$

where *seek* is an indicator variable equal to 1 if the individuals seeks information about his performance in the test, and zero otherwise. Φ is the cumulative normal distribution. We estimate the equation separately for the IQ and Numeracy tests. Our variable of interest is stated belief of the individual $q \in \{1, 2, \ldots, 5\}$ regarding the most likely quintile. The vector of control variables x includes controls for test performance. We estimate a five-part linear spline in test performance,

TABLE 4
The demand for information: IQ test

	(1)	(2)	(3)	(4)	(5)
q_i^{IQ} after test	0.031***	0.029***	0.029***		0.029***
	(0.009)	(0.009)	(0.008)		(0.010)
q_i^{IQ} before test				0.018**	−0.004
				(0.009)	(0.011)
q_i^{NT} after test					0.005
					(0.007)
Piece-wise linear profile in test score					
First quintile	0.000	0.000	0.000	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Second quintile	0.001	0.000	0.000	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Third quintile	0.017	0.016	0.015	0.018	0.014
	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
Fourth quintile	−0.008	−0.006	−0.007	−0.007	−0.007
	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)
Fifth quintile	0.006	0.006	0.006	0.010	0.006
	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)
Harm avoidance		−0.003**	−0.003**	−0.004**	−0.003**
		(0.002)	(0.001)	(0.002)	(0.001)
Social closeness		0.002*	0.002	0.002	0.002
		(0.001)	(0.001)	(0.001)	(0.001)
Social potency		−0.001	−0.001	−0.000	−0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Stress reaction		0.000	0.000	−0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Demographic controls?	No	No	Yes	Yes	Yes
p	0.000	0.001	0.003	0.003	0.005
N	838	838	826	825	825

Dependent variable: demand information (=1); marginal effects from probit estimates.
Notes: The model estimated here is described in Section 5, see in particular equation (8). ***, **, * indicate significance at the 1, 5, 10% level, respectively.

with the splines defined over quintiles in order to control for test performance in a flexible way. We also include personality characteristics as measured by the MPQ described earlier (Patrick *et al.*, 2002). We include personality traits to rule out the possibility that other personality characteristics that may affect confidence and curiosity at the same time, and thus bias our estimates. Because we have no strong prior, we include all 11 traits in the MPQ. Our estimates also include a large set of controls for socio-demographic differences across subjects: five dummy variables for education levels, five categories for ethnicity, a gender dummy, age and age squared, and household income.

The results are displayed in Tables 4 and 5 for the demand for information about one's performance in the IQ and Numeracy test, respectively. The table displays marginal effects on the probability of seeking information, rather than the bare coefficient estimates. Both tables are structured the same way. In the first column, we test whether, as indicated by the figure, a higher belief increases the likelihood of demanding information. Column (1) in Table 4 controls for test performance using a flexible functional form. It shows that conditional on actual performance, the subject's belief about their performance predicts whether or not he seeks information. More optimistic beliefs increase the likelihood of seeking information: a one-quintile increase in beliefs is associated with a 3% point higher probability of demanding information about the test. The

TABLE 5
The demand for information: Numeracy test

	(1)	(2)	(3)	(4)	(5)
q_i^{NT} after test	0.060***	0.057***	0.059***		0.040***
	(0.010)	(0.011)	(0.011)		(0.013)
q_i^{NT} before test				0.063***	0.018
				(0.013)	(0.017)
q_i^{IQ} after test					0.028**
					(0.014)
Piece-wise linear profile in test score					
First quintile	0.022	0.022*	0.022	0.029**	0.022*
	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)
Second quintile	−0.006	0.001	0.002	0.011	0.003
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Third quintile	0.011	0.009	0.010	0.017	0.008
	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Fourth quintile	0.003	0.008	0.016	0.021	0.017
	(0.041)	(0.040)	(0.039)	(0.039)	(0.039)
Fifth quintile	−0.001	0.009	0.013	0.019	0.008
	(0.048)	(0.045)	(0.044)	(0.043)	(0.045)
Harm avoidance		−0.005**	−0.005*	−0.005**	−0.004*
		(0.002)	(0.002)	(0.002)	(0.002)
Social closeness		0.003	0.002	0.002	0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Social potency		−0.000	0.001	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Stress reaction		0.002	0.002	0.001	0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Demographic controls?	No	No	Yes	Yes	Yes
p	0.000	0.001	0.003	0.005	0.005
N	888	886	873	873	873

Dependent variable: demand information (=1); marginal effects from probit estimates.
Notes: The model estimated here is described in Section 5, see in particular equation (8). ***, **, * indicate significance at the 1, 5, 10% level, respectively.

results are even stronger (see Table 5) for the Numeracy test, where a one-quintile increase in the belief leads to almost a 6% point increase in the likelihood of seeking information. In both cases, the effects are statistically highly significant.

Column (2) adds personality traits as controls, obtained from the MPQ. The only significant trait is harm avoidance, a measure of the relative preference of individuals for less risky situations. The effect is negative and small, and lends itself to a plausible interpretation that individuals who are less risk-averse are more likely to seek information, preferring the extreme values to their expected value. In column (3), we add the socio-economic control variables. However, they have no effect on the coefficient of interest. As a robustness check in column (4), we use the belief before the test as the independent variable to explain the demand for information. In both tests, the belief before the test is significant as well. As a final step, we build on this last specification to examine whether it is the current belief the subject holds that determines the demand for information, or just some general notion of confidence that may be reflected in all of the beliefs. Therefore, we also add the beliefs about the ability before the test as well as the beliefs about the ability in the other test as explanatory variables. Some individuals do change their evaluation over the course of the test (correlation between pre- and post-test beliefs: $\rho=0.64$ for IQ and

$\rho = 0.74$ for Numeracy). Similarly, while beliefs are correlated across tests, they are not perfectly correlated ($\rho = 0.54$ for beliefs after the test). This allows us to examine the specificity of the link between beliefs and the demand for information. Our results show that the link is highly specific. In Table 4, we see that only the most recent belief is significantly correlated with the demand for information. Confidence in the Numeracy test is uncorrelated with the demand for information about IQ, and so is confidence before the test, *ceteris paribus*. Our results are slightly weaker for Numeracy, where we find a weak effect of confidence in IQ on the demand for information about relative performance.

Overall these results are not supportive of the basic mechanism that generates overconfidence in models of self-image concerns (Kőszegi, 2006; Weinberg, 2006). However, the prediction that self-image concerns lead to avoiding information when beliefs are high critically hinges on the assumption that the information in itself has no economic value. If it has, only a weaker prediction holds: if there are economic benefits to seeking information, then individuals with a sufficiently optimistic belief (such that $\Pr(t \leq \hat{t}) \approx 0$, will now also seek the information, as it is very unlikely that they have to revise their believe downward. Adding economic value to the information still makes individuals with very low beliefs (*i.e.*, with $\Pr(t \leq \hat{t} \approx 1)$ seek information—just as in the baseline model, they can only gain from it. Thus, in this case, self-image concerns predict only an "inflection" of the demand for information as a function of beliefs around $\Pr(t \leq \hat{t}) \approx x$. The model can still generate overconfident judgements, but demand for information is now possibly just as strong at the top as it is at the bottom of the belief distribution.

In order to explore this, we re-estimate our specification with all the control variables in place, but now allow the beliefs to have non-linear effects on the demand for information by estimating a separate coefficient for each quintile, with the first quintile being the reference group. The results are displayed in Table 6, with column (1) displaying the results for the IQ test, and column (2) displaying the results for the Numeracy test. In both columns, there is no detectable deviation from the monotonic pattern that we found in Tables 4 and 5, and no inflection as predicted by a generalized version of the model with self-image concerns. This is particularly clear in the demand for information in the Numeracy test, but also visible in the case of the IQ test, though with somewhat less precision.[8] We also test formally whether the bottom two quintiles, whose point estimates are always lower than the top two quintiles, are significantly different from the the top two quintiles, and we reject equality in each case: in each test, the bottom two quintiles have significantly lower demand for information than individuals with higher beliefs Finally, we test whether the linearity in beliefs imposed in Tables 4 and 5 is supported by the data, and find that the restriction is easily supported with p-values of 0.15 and 0.29 for the IQ test and the Numeracy test, respectively.

Thus, our results indicate that individuals with higher beliefs have a monotonically higher demand to learn more about their ability. This raises the question of how overconfidence comes about in our subjects. The previous section has tested models of Bayesian updating, with common priors and truthful reporting of one's belief. This section focused on a prominent mechanism—the selective demand for information due to self-image concerns—independently of the common priors assumption. Neither mechanism can explain the overconfidence observed in our sample.

8. As can already be seen in Figure 1, there are only about 7% of all individuals who think they are in the bottom two quintiles in the IQ test. This renders any comparison to that group less sharp. In the case of the Numeracy test, our precision is greater, as we have about 15% of the observations in the bottom two quintiles.

TABLE 6

The demand for information: indicator variables for each belief quintile

	IQ	Numeracy
Second quintile (DV)	0.016	0.079**
	(0.037)	(0.023)
Third quintile (DV)	0.002	0.088**
	(0.052)	(0.031)
Fourth quintile (DV)	0.032	0.125***
	(0.043)	(0.022)
Fifth quintile (DV)	0.075*	0.223***
	(0.045)	(0.043)
Test of joint zero effect	$p<0.01$	$p<0.01$
Test that two top quintiles are different from the two bottom quintile	$p=0.06$	$p<0.01$
Test of linearity restriction	$p=0.15$	$p=0.30$
N	826	875

Dependent variable: demand information (=1); marginal effects from probit estimates.

Notes: The control variables are the same as in Tables 4 and 5. The bottom quintile is the reference group. ***, **, * indicate significance at the 1, 5, 10% level, respectively.

6. SOCIAL SIGNALLING AS THE SOURCE OF OVERCONFIDENCE

In this section, we explore a model that relaxes the assumption that individuals report their belief truthfully, and instead assume that they may misstate it in a motivated way. Some individuals may have a strict preference for the outside world to have has a positive view of their qualities, given the signals that individuals send. This preference may give produce a *socially rooted bias* in the stated confidence judgements. Such a preference on what others think may well be due to the interest an individual has in strategically influencing such judgements.

If we maintain a rational expectations assumption, this theory necessarily requires heterogeneity among individuals in how much they care about what others think of them. If all individuals had the same incentives to overstate their abilities, a rational outside world never would infer anything from these statements, and thus there would be no point in making them. We spell out a simple model that captures this intuition and provides us guidance on costs and benefits of overstating one's abilities. We then measure individuals differences in these benefits and costs with specific personality traits predicted by our theory, as measured by the Minnesota Personality Questionnaire (MPQ). Conditional on a large set of controls, this allows us to test whether individual differences in these traits predict differences in overconfidence.[9] The same model also provides a psychological mechanism that makes individuals look as if they perceived information in a biased way (as, *e.g.*, in Daniel *et al.*, 1998). However, as our model makes clear, no additional argument is needed to explain this pattern. Individuals who overstate their abilities will not respond fully to new information available. They have an incentive to overstate their abilities and therefore will never fully adjust their statements to new information. They look as if they perceived information in a biased way, when, in fact, it is the reporting that is biased.

9. Differences in personality could also affect the type of information individuals seek. But this alone cannot explain overconfident judgements, as individuals should properly discount the fact that different individuals seek different information in forming their beliefs.

Our theory makes the prediction that those same personality traits that predict overconfidence should also predict who adjusts to the arrival of new information.

6.1. *A simple model*

The model we consider is a signalling game in a game with large population of players. Each player chooses a signal, the public observes it and updates the belief on the skill of that player. Individuals have good reason not to lie, because by doing so they incur a cost, which in our experiment is the missed payment occurring when the statement deviates from what they think is the truth. This is a standard signalling game, with one important twist: there is an externality among agents, because the public updates taking into account the behaviour of the entire population, so the solution is an equilibrium in the population.

Formally, we consider a large population where each agent is assigned a skill parameter, denoted $\theta \in \Theta$, a finite set, and a function γ measuring how much he cares about the belief of others. The draw follows a prior distribution μ. Each agent observes privately a signal x on his pair (θ, γ). A simple case that we will focus on is the one in which he knows the pair. He then chooses a social signal s that is observed by all. People update their beliefs on that agent's distribution on the skill parameter θ, and this updated belief enters into the utility of the individual, which has the form:

$$u(\theta, s) + \gamma(\mu(\cdot|s)). \tag{9}$$

In the data analysis, γ is measured by the personality traits, such as social potency, and the θ by the IQ test. The signal s is the statement subjects give on the quintile of their score. We restrict the utility function u to make lying costly, to model the monetary incentive we give to the subjects. This function might also include psychological and social norm costs.

To reflect the monetary costs in our experiment, we make $S = \Theta$ and assume

$$\max_s u(\theta, s) = u(\theta, \theta).$$

maximize utility when the social signal
is the same of the private one

The function γ is only assumed to be increasing in the belief. The specific model we discuss here is very simple: the main purpose we want to accomplish is to show that individual differences is both skills and preferences over social image can produce an equilibrium where individuals who attach larger importance to image give, ceteris paribus, a higher statement. The choice of an environment with only two skill and two preference types allows us to show that the equilibrium is unique. We can also explicitly compute the equilibrium, so that the comparative statics and the proof of our claims are immediate. We comment below on how these results generalize to richer models.

We take $\Theta \equiv \{0, 1\} = S$, $\Gamma = \{0, 1\}$, both known to the individual. The utility of giving the right signal is $a > 0$, the wrong signal has utility 0. The utility of the belief is equal to the expected value of the parameter θ for the individual, multiplied by γ.

The equilibrium of this game is straightforward. A strategy is a map from pairs (θ, γ) to the signal, such that each individual wants to give the signal assigned by the strategy. Three of the four types have deterministic strategies. The types $(0,0)$ and $(1,0)$ do not care about the public opinion, so since lying is costly they say the truth, and signal 0 and 1, respectively. Players of type $(1,1)$ do not want to make themselves appear less capable than they really are, so they signal 1. The fixed point is run for the type $(0,1)$: a fraction p of them might want to lie. We now find the equilibrium value of p.

Upon observing $s=1$, the posterior of the public on the pairs is

$$\mu((0,0)|s=1)=0,$$

$$\mu((1,0)|s=1)=\frac{\mu(1,0)}{\mu(1,0)+\mu(1,1)+p\mu(0,1)},$$

$$\mu((0,1)|s=1)=\frac{p\mu(0,1)}{\mu(1,0)+\mu(1,1)+p\mu(0,1)},$$

$$\mu((1,1)|s=1)=\frac{\mu(1,1)}{\mu(1,0)+\mu(1,1)+p\mu(0,1)},$$

and therefore the posterior on θ is

$$\mu(\theta=1|s=1)=\frac{\mu(1,0)+\mu(1,1)}{\mu(1,0)+\mu(1,1)+p\mu(0,1)},$$

a function of p which is decreasing, continuous. $\mu(\theta=1|s=0)=0$, of course. The unique value of p for which the type $(0,1)$ is indifferent between lying, signalling $s=1$ and getting no u-utility but the social image utility and stating the truth and getting a utility, but zero social image is the equilibrium. If no p exists to give equality, then either all individuals of type $(0,1)$ lie (a very low) or all say the truth.

In summary, the equilibrium of the social signalling game is unique (completely characterized by the p). When the utility of not lying (a) is small enough (our dollar and few cents) there is overconfidence and only overconfidence (and no underconfidence). Also all types of low ability and high social potency (the $(0,1)$ types) are overconfident, so overconfidence is positively correlated with high social potency. The equilibrium has intuitive properties: people who care about social beliefs are tempted to make an overstatement, to increase the good opinion of others. With no heterogeneity of types in the personality dimension, the overstatement would not be believed, and would not be made at equilibrium because lying is costly (in our experiment the failure to predict well the relative performance decreases one's payment). But if there is heterogeneity then people who care less will make a honest statement, and those who care will free ride on them because on average the statement made carries some information. The externality is clear: if more low-skilled individuals overstate their ability, the signal is less reliable. In some sense this also means that there is an equilibrium limit to the lie.

The main features of the equilibrium described here are preserved in more general formulations, in particular in the model where the type and signal set have more than two elements. An equilibrium exists (for every u, γ), because the game is finite. Consider games where the prior μ assigns equal probability to all pairs of skill and preference types. In all equilibria individuals who attach no value to social image report the true skill type, because their only motivation is the payment measured by the function u. Thus all skill types are stated with positive probability, and thus the posterior on the individual's skill type for any statement, is in all equilibria produced by Bayes' rule. Thus the equilibria of the model satisfy most reasonable equilibrium refinements.

The truth-telling strategy profile is an equilibrium and unique when the cost of lying is high enough compared to the social image value, because the gain from deviating to the true statement would override the gain in social image even from the highest type. On the other hand, the truth-telling is never an equilibrium when the cost is small enough, because when all other players are playing the truthful strategy the gain in social image from deviating to a statement higher than the truth is larger than the cost of a smaller payment. When the cost is small but non-zero, the high skill type tells the truth in all equilibria, and the lowest skill type makes overconfident statements in all equilibria. Also in this case an equilibrium exists where individuals only state a type higher or equal to their true type (and never a lower type), and the probability distribution on the signal space in increasing in first order stochastic dominance in the true type.

6.2. *An empirical test: overconfidence as a function of personality traits*

The main hypothesis we derive from our simple model is that subjects differ in the strength of preference for a positive view that others have about them. Those who care strongly about what other people think are more inclined to send a signal about their skills this it more positive than their information would warrant, even at some cost. In our experiment the cost is reducing the probability of obtaining the monetary prize: but there are of course many social costs that are attached to such discrepancy. Perhaps the underlying psychology is that these subjects process the information they have received in a biased manner for this social reason, and thus misrepresent their real skill to themselves. Or, it may be that they strategically lie, misleading others, but not themselves. We do not suggest one of these two possibilities is exclusively correct. Probably a little of both is true in the population, and perhaps to some degree also in many individuals. As Bénabou and Tirole (2002) suggest, a very good way to lie to others is to lie to yourself first. What is crucial to our hypothesis (and this is the reason for describing it as social signalling) is that the main motivation for a misrepresentation is that it affects the individual's social standing.

In our experiment they would cooperate more

We test this model by focusing on dimensions that can readily be measured using well-established personality scales, such as the MPQ discussed earlier in Section 2. In our model, some individuals derive utility from others believing they have high ability. We operationalize this desire by the social potency scale from the MPQ. It measures the extent to which an individual likes to dominate others, likes to influence others, and derives pleasure from being in the public limelight. Individuals who score high on social potency should attribute more importance to the belief of others about their ability. Our model therefore predicts that they should display stronger overconfidence. An important concern in this context is separating the desire of a dominant position from other social motivations or from an absolute desire to achieve. The *MPQ* also allows us to distinguish this from a more general desire to be connected to others, which is measured in the social closeness scale. The *MPQ* also allows us to distinguish the desire to dominate from general drive to achieve, by including the achievement scale as a control.

The second element in our model is that individuals have a disutility from overstating their ability. This may be thought of as being "caught" exaggerating, in public with all the negative social feedback this entails. The *MPQ* contains the stress-reaction scale, which measures precisely this aspect of personality: whether the individual is prone to worrying and whether he reacts strongly to negative social feedback. Thus, our model predicts that individuals who score high on stress reaction will suffer more from misstating their abilities and should display less overconfidence. The *MPQ* also allows us to control for other aspects of risk preferences, such as a more general tendency towards prudence, as measured by the harm avoidance scale, and general pessimism captured by the Alienation scale.

The predictions with respect to social potency and stress reaction follow directly from the static formulation of our model. However, a dynamic version of our model may make additional subtle predictions with regard to how stress reaction and social potency influence a sequence of confidence judgements. We return to these in later. Figure 5 provides a first impression of the main predictions. It shows relative ability judgements and actual abilities for individuals who have different scores in personality traits. Each panel reflects a different personality trait. In each case, we cut the sample by the median trait score. For example, in Panel A, the first graph shows that about 30% of the individuals scoring below the median in social potency think they belong to the top quintile of the IQ distribution. In contrast, 55% of the individuals scoring above the median

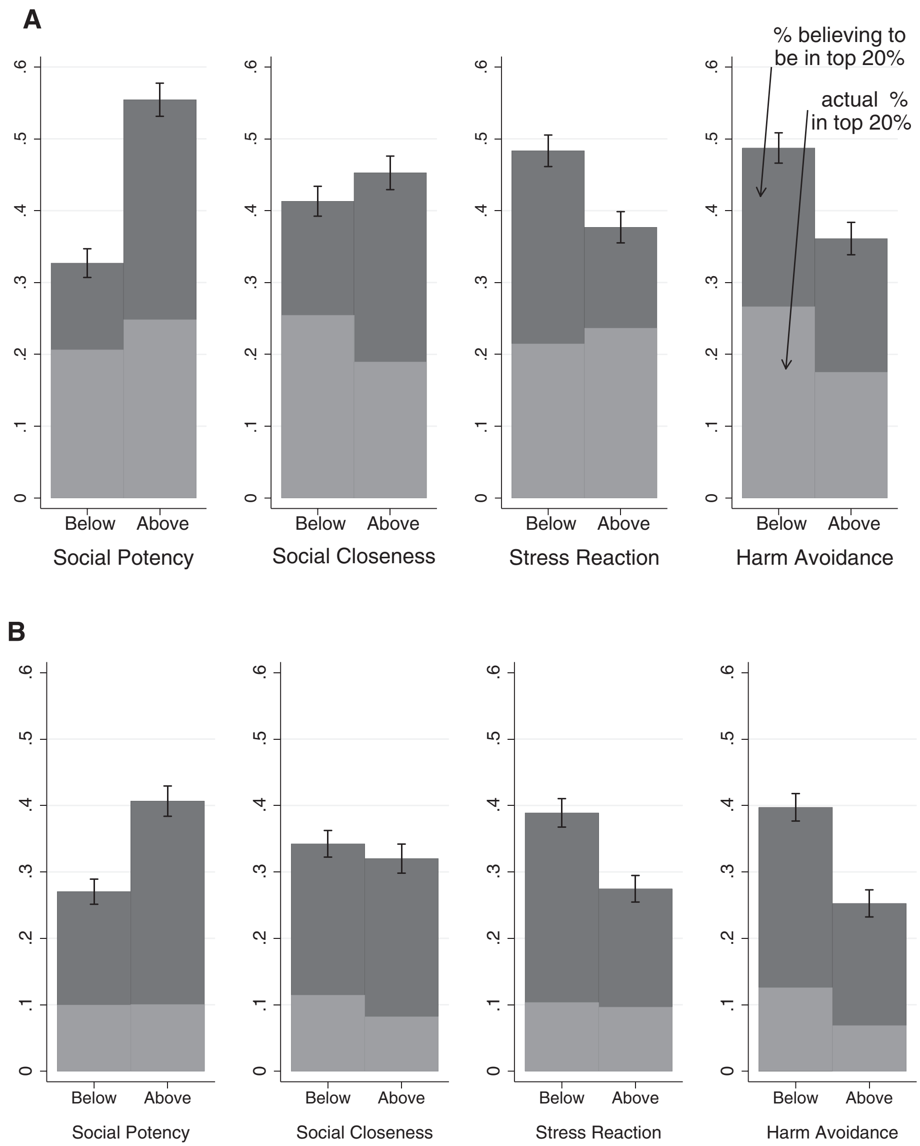

FIGURE 5

Personality characteristics and relative performance judgements. Panel A: IQ. Confidence judgements in IQ test as a function of the strength of trait relative to the median. Panel B: Numeracy. Confidence judgements in Numeracy test as a function of the strength of trait relative to the median

Notes: Caps indicate standard error of the respective mean.

in social potency think they are in the top quintile. Each graph also contains the actual fraction of individuals scoring in the top 20% for each subsample, in lighter blue super imposed. The graph shows virtually no difference between high- and low-social potency individuals in terms of actual ability. The results for relative ability judgements in the Numeracy test are very similar. Thus, social dominance appears to pick up quantitatively important differences in the overconfidence of judgements, while being unrelated to differences in actual abilities. Turning to the graph that cuts the sample by social closeness, we see no differences in relative ability judgements. Thus, it appears that individuals who care more about sociability are not more confident in general; the relationship is limited to the aspect of dominance relative to others. The third graph cuts the sample by the median of the stress-reaction score. Individuals who are highly sensitive to social stress have substantially more timid judgements about their ability, as can be seen in the graph, while this is again not related to differences in actual abilities. Again, a very similar pattern emerges when we examine relative ability judgements regarding the Numeracy test in Panel B.

In order to examine these hypotheses using a formal statistical test, we proceed in two steps to make transparent the role of the econometric structure imposed in the estimation. In a first step, we estimate an ordered probit model of *confidence* judgements as a function of personality traits. The individual believes his most likely quintile is $b_i = k$ if

$$\alpha_k \leq \gamma' MPQ_i + \beta' x_i + \epsilon_i < \alpha_{k+1}, \tag{10}$$

where $1 \leq b_i \leq 5$ is the individual's belief about his most likely quintile. *MPQ* is the vector of 11 personality traits, and x is a set of control variables, α_k are the judgement cutoffs, and ϵ_i is a standard normal residual. This gives rise to an orderd probit model that can me estimated by maximizing the likelihood

$$\Pr(b_i = k | MPQ_i, x_i) = \Phi(\alpha_{k+1} - \gamma' MPQ_i - \beta' x_i) - \Phi(\alpha_k - \gamma' MPQ - \beta' x). \tag{11}$$

The function $\Phi()$ is the cdf of the standard normal distribution. This specification allows us to test whether, conditional on a broad set of controls, personality characteristics affect confidence judgements in the predicted way.

In a second step, we then impose additional structure and estimate an ordered probit model of *overconfidence.* Our theory predicts relationships between personality traits and overconfidence, and it is desirable use this additional structure to perform a stronger test. We model over- and underconfidence in an ordered model where the difference between individual i's confidence judgement b_i and his actual ability q_i is $b_i - q_i = k$ if

$$\alpha_k \leq \gamma' MPQ_i + \beta' x_i + \epsilon_i < \alpha_{k+1}. \tag{12}$$

This implies for the probability of $b_i - q_i = k$

$$\Pr(b_i - q_i = k | MPQ_i, x_i) = \Phi(\alpha_{k+1} - \gamma' MPQ - \beta' x) - \Phi(\alpha_k - \gamma' MPQ - \beta' x), \tag{13}$$

which we estimate by maximum likelihood. However, we also need to take into account the truncation of $b_i - q_i$ induced by the actual ability q_i. In this specification of the model, individuals of the top quintile cannot overestimate their ability, thus if $b_i - q_i = 0$ for $q_i = 5$, we only know that $\gamma' MPQ_i + \beta' x_i + \epsilon_i \geq \alpha_0$ (and not $\alpha_1 > \gamma' MPQ_i + \beta' x_i + \epsilon_i \geq \alpha_0$). Similarly, individuals with $q_i = 4$ can only overestimate their ability by one quintile, and we take this into account analogously. See the Appendix for details.

A crucial question is whether the estimated correlations between our personality traits of interest, social potency and stress reaction, can be interpreted in a causal influence from personality traits to overconfidence. There are two issues that we need to consider: omitted variables and reverse causality. Omitted variables can bias our estimates if they are correlated with overconfidence and with the personality trait of interest. We feel confident that we address this problem in a satisfactory way: we include a very flexible functional form for the actual performance in the IQ and Numeracy test, thus ruling out that differences in cognitive ability that may be correlated with overconfidence and personality at the same time, biasing our estimates. We also include a rich set of demographic variables that capture differences in social background. Finally, the inclusion of the remaining nine personality traits allows us to partial out the specific factor that we are interested in, whereas all other traits absorb related, but distinct, effects of personality on overconfidence that may be inconsistent with our model.

The second issue is reverse causality. Reverse causality is unlikely to be an issue in this case. First, for the specific traits in question, we find it difficult to see what plausible theory would predict that overconfident beliefs would lead an individual to *develop* these personality traits. To take the specific example of social potency, a number of questions ask the respondent whether he likes to dominate others, and whether he enjoys visibility in social contexts (see, *e.g.* Patrick *et al*., 2002). It is hard to see how overconfident beliefs would cause individuals to have such a preference. Overconfident beliefs should often lead to embarrassing social feedback (because the individual is too confident in his abilities). If anything, overconfidence should cause a desire not to be too visible. A similar argument applies for the case of stress reaction. On the other hand, the direction of causality that our theory postulates is very plausible. Second, the statistical properties of personality traits and overconfidence also suggest the direction of causality that our theory postulates. Personality traits have a very strong genetic component, and are very stable over time. Blonigen *et al*. (2003) show that the correlation in stress reaction and social potency is around 0.5 between monozygotic twins, and virtually zero among dizygotic twins. In a longitudinal study, Roberts *et al*. (2001) show that those same personality traits have a within-individual correlation of about 0.5 when measured at the age of 18 and at the age of 26. In contrast, overconfidence is known to vary strongly between experimental conditions (Hoffrage, 2004; Hoelzl and Rustichini, 2005). Even within our subjects, the spearman's rank correlation of overconfidence judgements is only 0.19 between the two tests. How an extremely volatile variable can cause a variable that has a very strong genetic component and has been shown to be stable over time adds to the plausibility problem of a reverse causality. Thus, while we are aware that cross-sectional studies can never fully rule out problems of omitted variables and reverse causality, the specific setup makes it unlikely that this is a concern in this case.

6.3. *Results*

Table 7 presents the results from the model of confidence judgements, as specified in equations (10) and (11), displaying directly the marginal effects on believing that one is in the top 20%, for confidence judgements in the IQ test in columns (1)–(3), and the Numeracy test in columns (4)–(6). The first column in each group presents the partial correlations with the only the personality traits included. While social potency and stress reaction are both significant with the predicted sign, other personality traits are significant, as well in contrast to what we expected (in particular, absorption, traditionalism, and social closeness). However, as we progressively include more stringent controls, these variables are no longer significant. In our strictest specification (in columns (3) and (6), respectively), social potency and stress reactions still have their predicted sign (together with harm avoidance in the specification for IQ, which is also consistent with our model). Differences in the personality traits of social potency and stress reaction have quantitatively large effects on confidence, conditional on all of our controls. An increase of 8 index points for social potency (social potency's interquartile range) increases the probability that the individual thinks he is in the top 20% of the distribution by 8.8% points, while an increase of 9 index points for stress reaction (stress-reaction's interquartile range) reduces the probability that the individual thinks he is in the top 20 percent of the distribution by 7.2 percentage points.

TABLE 7
Personality characteristics and confidence judgements

	Confidence in IQ test			Confidence in Numeracy test		
	(1)	(2)	(3)	(4)	(5)	(6)
Absorption	0.007**	0.005	0.005*	0.004*	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Achievement	0.004	−0.001	−0.001	0.004	−0.003	−0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Aggression	0.000	−0.001	0.000	−0.002	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Alienation	−0.004	0.000	0.001	−0.007**	0.004	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Control	−0.001	0.001	0.001	−0.001	0.003	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Harm avoidance	−0.009***	−0.008***	−0.007**	−0.007***	−0.006**	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Social closeness	−0.007***	−0.004	−0.003	−0.007***	−0.004	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Social potency	0.014***	0.013***	0.011***	0.013***	0.013***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Stress reaction	−0.007***	−0.009***	−0.009***	−0.006***	−0.007***	−0.007***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Traditionalism	−0.007**	0.000	−0.001	−0.004	−0.001	−0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wellbeing	−0.003	−0.002	−0.001	−0.009	−0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Skill controls?	No	Yes	Yes	No	Yes	Yes
Demographics?	No	No	Yes	No	No	Yes
F-test for joint significance of personality traits	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$
Pseudo-R^2	0.05	0.16	0.17	0.03	0.17	0.19
N	1062	1015	1015	1063	1063	1063

Marginal effects on the probability of in the top 20% from ordered probit model.
Notes: The model estimated here is described in Section 5, see in particular equation (8). ***, **, * indicate significance at the 1, 5, 10% level, respectively.

We now turn to the estimates of the impact of personality traits on our direct measure of overconfidence, as specified in equations (12) and (13). The results are presented in Table 8, calculating directly the marginal effects for being overconfident. Although the identification of the personality traits on overconfidence in equation (10) was achieved by conditioning on actual performance, the results here are identified directly by the difference between the belief b_i and the actual ability q_i. The results in all three columns and for both measures of overconfidence (IQ and Numeracy test) closely parallel those in Table 7, but display the specificity of social potency and stress reaction for overconfidence even more strongly.

The estimates conform well to our theory. Even though we include the entire set of personality characteristics and some aspects are highly correlated, we find highly specific effects exactly as predicted by the theory. In contrast to the estimates based on equation (10), specifying the model directly in terms of overconfidence makes the estimates more stable and less dependent on the conditioning variables. It is also worth pointing out that the results show a very strong specificity of personality traits for overconfidence. For example, the results show that it is the desire to dominate

TABLE 8
Personality characteristics and overconfident judgements

	Overconfidence in IQ test			Overconfidence in Numeracy test		
	(1)	(2)	(3)	(4)	(5)	(6)
Absorption	0.000	0.003	0.004	0.001	0.002	0.002
	(0.003)	(0.012)	(0.002)	(0.003)	(0.003)	(0.003)
Achievement	−0.004	0.000	0.000	−0.005	−0.004	−0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Aggression	−0.003	−0.002	−0.001	0.000	−0.001	−0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Alienation	0.005*	0.000	0.002	0.005*	0.003	0.004
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Control	0.000	0.001	0.000	0.002	0.002	0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Harm avoidance	−0.004	−0.005***	−0.005**	−0.004	−0.005*	−0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Social closeness	−0.002	−0.004*	−0.003	−0.003	−0.004	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Social potency	0.009***	0.010***	0.008***	0.012***	0.013***	0.010***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Stress reaction	−0.005**	−0.007***	−0.007***	−0.006***	−0.006***	−0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Traditionalism	0.003	0.000	0.000	−0.001	−0.002	−0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Wellbeing	0.003	−0.002	−0.001	0.002	0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Skill controls?	No	Yes	Yes	No	Yes	Yes
Demographics?	No	No	Yes	No	No	Yes
F-test for joint significance of personality traits	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p=0.01$	$p<0.001$
Pseudo-R^2	0.01	0.24	0.25	0.02	0.05	0.06
Log likelihood	−1463.912	−1129.03	−1117.221	−1317.37	−1282.838	−1265.65
N	1062	1012	1012	1060	1060	1060

Marginal effects on the probability of being overconfident from modified ordered probit model.
Notes: The model estimated here is described in Section 5, see in particular equation (8). ***, **, * indicate significance at the 1, 5, 10% level, respectively.

others that is predictive of overconfidence, not the desire to socialize with others (social closeness) or the desire to perform well (achievement). Even though social potency and social closeness are strongly correlated ($\rho=0.39$) as well as achievement ($\rho=0.23$), it is only social potency that is predictive of being overconfident. Similarly, stress reaction and general pessimism (alienation) are highly correlated ($\rho=0.58$), yet it is only stress reaction that is predictive of less overconfidence. A final way to assess the specificity of the effects is to ask if stress reaction and social potency were also significant if one took the agnostic null of no relationship between personality characteristics and overconfidence. With 11 variables in a regression, by the definition of the 5% significance level, there is a much higher chance that some are significant than 5%. First, notice that an F-test that the coefficients γ of the personality traits are zero is overwhelmingly rejected ($p<0.001$ in all cases). Second, we can also apply the Holm (1979) correction to adjust the critical values to 11 hypothesis tests. Even when we apply this correction, stress reaction and social potency are still significant at the 1% level for overconfidence in the Numeracy test. In the estimation results for the IQ test, with the correction, social potency is still significant at the 1% level, and stress reaction is significant at the 6% level. Again, we find a quantitatively large effect of of social potency and stress reaction on overconfidence. Even conservative estimates (in columns (3) and (6), respectively) show that by raising social potency (stress reaction) by it's interquartile range, increases the probability that an individual makes an overconfident judgement in the IQ test by 6.3 (6.4) percentage points for social potency (stress reaction). The quantitative implications are very similar for overconfidence in the Numeracy test.

As a further robustness check, we also estimate equation (12) for each quintile separately.[10] This also assures the correct definition of the top and bottom categories in each ability quintile, but it allows all the coefficients in the model to differ across quintiles. As the sample is cut down to 20% for each equation, we lose precision and the standard errors must be expected to increase by a factor of $\sqrt{5}=2.24$. Still, we find that for 19 of the 20 estimated coefficients for stress reaction and social potency, the sign is as expected. Importantly, the estimations reveal no obvious fragility, or patterns inconsistent with our model in any of the quintiles. The average coefficient across all five quintiles remains highly significant for stress reactions and for social potency, in the equations for IQ and for Numeracy ($p<0.01$ in all cases). There is also some evidence that the effects of personality are stronger for the 3rd, 4th, and 5th ability quintile, especially for social potency (see Burks *et al*., 2010, for details).

6.4. *The revision in beliefs*

Our model predicts that individuals know their type with certainty, and yet some individuals who know they are of the low type state a belief that they are high type. To model the response to new information coming after their first statement the model can be extended to include a case where individuals do not know their type and they only observe an informative signal on it. As in the previous case where individuals know their type, those who care more about the public belief will, for the same private signal, give a more confident statement about their performance than those who care less. If as in our experiment the statement has a discrete set of values, cutoffs in the signal space will determine what statement they make.

Suppose now that an additional information is provided to them: in our experiment, this additional information is the IQ test itself, that gives them a concrete idea about what the test is. Each individual will use this additional information, and use it to revise their estimated performance. How will personality affect this revision? A subject who does not care about public belief will revise the statement down, if the test is harder than he thought, to maximize the probability of a reward. A subject who does, and has given a high statement, may consider revising the statement because now maximizing the expected payment for correctly anticipating his own performance requires that. However, a revised statement would reveal at equilibrium that his previous high statement was originated by a private signal close to the lower end of the interval in private signal space for which individuals are expected to provide that signal. This loss of reputation will make them more reluctant to revise their statement. In conclusion, our model of overconfidence as a public signal provides a clear prediction on the revision of statements made by participants after they have seen the test: the more an individual cares about the inferences others make about him, the more he/she should be reluctant to revise their stated beliefs in response to new information. In particular, a high score of social potency should reduce the likelihood to respond to new information by changing the statement. The converse argument for stress reaction produces the prediction that a high score in stress reaction should lead to more revisions.

10. The details of the estimation results are omitted here, but can be found in full length in Burks *et al*. (2010).

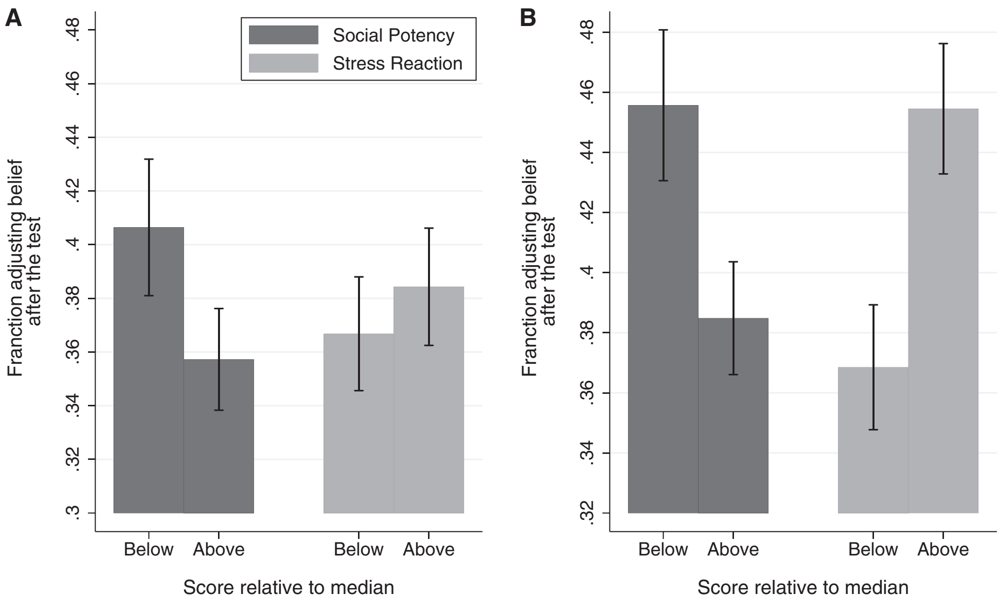

FIGURE 6

Stated beliefs before and after the test, for high and low values (with respect to median) of social potency and stress reaction. (A) IO test; (B) Numeracy test

Notes: Bars indicate standard error of the respective mean.

Our experimental setup allows us to test this hypothesis. Because we asked individuals to state their confidence levels, both before and after they had taken the test, we can examine how taking the test affects the revision of the individuals' stated beliefs and relate this revision to traits. In the IQ test, 29% of subjects revise their belief downward, and 63% do not change it, so only approximately 7% revise their belief upward. For Numeracy, the percentages are 27% downward and 59% unchanged. The downward revision is, on average, significant ($p<0.001$ for each of the tests, Wilcoxon signed rank test). Thus, on average, taking the test produces information that leads about 30% of the individuals to revising their beliefs downward.

Does the tendency to revise one's belief depend on the two personality traits we have identified as affecting overconfidence? Figure 6 shows how the adjustment of beliefs depends on our two personality traits of interest, social potency, and stress reaction. Panel A displays the results for the IQ test, Panel B for the Numeracy test. Individuals who score high on social potency are less likely to adjust their beliefs as new information arrives. Similarly, individuals who score low on stress reaction are less likely to revise their beliefs. Thus, the same traits that are strongly associated with overconfidence in a cross-sectional analysis are also associated with a lower tendency to revise these beliefs. This is consistent with our conjecture that social potency and stress reaction may also influence how information is perceived.

In order to test this more formally, we estimate a probit model for whether or not an individuals revises his beliefs after the test:

$$\Pr(revise_i=1|MPQ_i,x_i)=\Phi(\gamma' MPQ_i+\beta' x_i), \tag{14}$$

where the notation is the same as in equation (12), and the control variables included in the same order of the columns as in Table 8. Table 9 displays the results, directly in the form of marginal

TABLE 9
Personality characteristics and revision of confidence judgements

	Change in confidence in IQ test			Change in confidence in Numeracy test		
	(1)	(2)	(3)	(4)	(5)	(6)
Social potency	−0.007*** (0.003)	−0.006** (0.003)	−0.006** (0.003)	−0.005* (0.003)	−0.005* (0.003)	−0.005* (0.003)
Stress reaction	0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
Skill controls?	No	Yes	Yes	No	Yes	Yes
Demographics?	No	No	Yes	No	No	Yes
F-test for joint significance of personality traits	$p=0.01$	$p=0.03$	$p=0.07$	$p<0.001$	$p<0.001$	$p<0.001$
Test that social potency and stress reaction have the same coefficient	$p<0.001$	$p=0.01$	$p=0.07$	$p<0.001$	$p<0.001$	$p<0.001$
Pseudo-R^2	0.01	0.03	0.05	0.01	0.05	0.06
N	1015	1015	1015	1063	1063	1063

Marginal effects from probit model.
Notes: ***, **, * indicate significance at the 1, 5, 10% level, respectively.

effects of revising one's judgement. It shows that our personality traits again significantly affect the decision to revise one's confidence judgement after having taken the test. Individuals who score high on social potency are much less likely to revise their beliefs after the test. Social potency has a significant effect on the probability to revise one's belief about, both, the IQ and the Numeracy test. In both cases, the estimates imply that in increase in the social potency score by 8 (the interquartile range), decreases the probability to revise one's confidence judgement by approximately 10 percentage points, a considerable effect. In the case of the stress-reaction scores, the results are only significant for the Numeracy test, though the point estimate are of the same sign also for the IQ test. In the case of the Numeracy test, the magnitudes are, again, substantial, with an increase of the stress-reaction score by the inter-quartile range leading to an increase in the probability to revise one's judgement by 12 percentage points. In all cases, we reject the hypothesis that personality traits play no role. We also test the somewhat weaker hypothesis that stress reaction and social potency, which our theory predicts should have opposite signs have the same sign. Not surprisingly, we also reject this hypothesis.

As a final step, we also explore whether the personality traits predict the direction in which the individuals adjust their belief. Given that most of the adjustment is downward, we define a new variable that is equal to 1 if the subject adjusted his belief downward and zero otherwise, and estimate the otherwise same model as in equation (14). The results are displayed in Table 10. The results are slightly weaker. We do have some support of our model because we can reject the hypothesis that the signs of the coefficients on social potency and stress reaction are the same, but we lose some precision in the estimation because we only consider downward revisions and thus lose variation in the data.

Overall, our results suggest that personality traits also influence how an individual processes information and adjusts his confidence judgements. Social potency makes individuals more prone to stick with their judgement, consistent with the notion that they feel dominant relative to the others. A higher score of stress reaction makes individuals more likely to adjust their judgements, consistent with the notion that these individuals worry more about making errors and therefore give more weight to the information they receive.

TABLE 10
Personality characteristics and downward revision of confidence judgements

	Change in confidence in IQ test			Change in confidence in Numeracy test		
	(1)	(2)	(3)	(4)	(5)	(6)
Social potency	−0.005*	−0.004	−0.004	−0.003	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Stress reaction	0.001	0.002	0.002	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Skill controls?	No	Yes	Yes	No	Yes	Yes
Demographics?	No	No	Yes	No	No	Yes
F-test for joint significance of personality traits	$p=0.09$	$p=0.14$	$p=0.22$	$p=0.11$	$p=0.23$	$p=0.16$
Test that social potency and stress reaction have the same coefficient	$p=0.04$	$p=0.05$	$p=0.08$	$p=0.04$	$p=0.09$	$p=0.05$
Pseudo-R^2	0.01	0.03	0.05	0.01	0.13	0.14
N	1015	1015	1015	1063	1063	1054

Marginal effects from probit model.
Notes: ***, **, * indicate significance at the 1, 5, 10% level, respectively.

7. CONCLUSIONS

We have examined in an experimental setup evidence for overconfidence of individuals about their intelligence in the light of three possible theories.

First, we tested and rejected the hypothesis that overconfidence results from incomplete information about one's own ability, Bayesian updating from a common prior, and truthful revelation (Benoît and Dubra, 2011). The test we use is general, and may be used to probe the same hypothesis in similar studies. In our data, the level of overconfidence in our subjects' statements is beyond what can occur in a world of truthful Bayesians.

Second, we tested and rejected the mechanism that optimistic beliefs about one's abilities lead individuals to avoid new information about their absolute or relative performance (Kőszegi, 2006; Weinberg, 2006). As an implication of this finding, we reject a central prediction of models of self-image management. These models assume that individuals derive utility directly from better beliefs about their own skills, and predict that when individuals optimally manage information acquisition those with better beliefs will be more reluctant to search and observe further information about their abilities. In our data the opposite is true: we find a positive and highly significant association between optimism of beliefs and demand for information about one's relative performance. This relationship is, as we have shown, specific to the belief about one's relative performance in the test at hand. Further, it is the belief after the test, not the belief about one's ability before the test, that predicts the demand for information. Individuals are more likely to demand feedback on performance when they have just received a positive impression of their performance, and this is precisely when self-image management concerns should lead to choosing ignorance.

Third, we test the hypothesis that individuals may overstate their abilities because they care about what an outside observer would think of them. Such *social* signalling only works if individuals differ in weight they attach to what outside observers think of them, thus opening the issue of how individual differences in personality affect overconfidence. We develop an illustrative model of such a mechanism. We show that specific measures of personality traits affect significantly the stated level of confidence (*i.e.*, the quintile of test performances in which the subject locates himself). The personality traits that affect the statement, and the direction of the effect, are consistent with the idea that the explanation of confidence is the social signal that positive confidence produces. Specifically, social potency, an indicator of personal inclination to a dominant role, strongly increases the probability that a subject is more overconfident. The personality trait stress reaction has the opposite effect, reducing the level of confidence. Both social potency and stress reaction affect the belief revision that takes place after subjects tried the test, in the expected direction: higher social potency makes individuals less willing to revise, higher stress reaction more willing to revise. Since the traits are likely to be constant over the experiment, it seems legitimate to say that they are in part a proximate cause of the difference in revisions.

In Bénabou and Tirole (2002)'s classification, optimistic self-assessment seems motivated by its signalling value, that is, by its potential effect on the opinion of others. As we mentioned earlier, the individuals who give optimistic self-assessment may believe what they say, or may try to deceive others: we do not advance either explanation to the exclusion of the other, and our data cannot really provide a way to separate them.

Our findings are consistent with the current re-evaluation of the importance of self-esteem as a predictor of individual performance and success. In recent years, a re-examination of the correlation between self-esteem and outcomes of interest has consistently found a weak relationship to school performance (Kugle *et al.*, 1983; Davies and Brember, 1999) and IQ (Gabriel *et al.*, 1994). In addition, the causal direction is likely to go from performance to self-esteem as much as it is going in the opposite direction. The survey in Baumeister *et al.* (2003) is a thorough discussion of the evidence in favour of a positive effect of self-esteem on a range of performance measures, including happiness and healthy lifestyle, and the overall conclusion is that the evidence of a causal relation is weak at best. Similar results are reported in other surveys (Mecca *et al.*, eds 1989; Leary, 1999). If the utility from positive self-image has no individual functional basis and a positive self-image offers no improvement in any significant performance index, then it is natural to consider the possibility that the roots of overconfidence lie in the value of over-confidence as a social signal (Leary and Downs, 1995; Leary *et al.*, 1995). These findings also point to the importance of personality traits in predicting economic and strategic behaviour (Rustichini, 2009).

APPENDIX

A. RESTRICTIONS IMPOSED BY THE BAYESIAN MODEL

We provide here the conceptual structure to set up the empirical test of the Bayesian hypothesis, that statements of individuals about their most likely percentile are produced by truthful reporting of Bayesian updating on the basis of private information.

Prior to the experimental session, each individual has observed in his lifetime a possibly complex signal on his intellectual abilities. These signals may include all sorts of different personal experiences: their success in school, on the job, in day to day comparison with others, including their speed in solving Sudoku games. All these signals are summarized in our model by a single observation. This signal is his private information, and is produced by an experiment (in the sense of statistical theory), which is a function from the set of types to distribution on signals. We take as set of signals the real line, X, endowed with the Borel σ-algebra $\mathcal{B}(X)$.

So the private experiment is: $(X, \mathcal{B}(X), (P_\theta)_{\theta \in \Theta})$ where for every θ, $P_\theta \in \Delta(X, \mathcal{B}(X))$, the set of probability measures on X. We do not know or observe the experiment P, so we are trying to estimate the most likely experiment given our data; and to test whether the overall hypothesis that the data are produced by Bayesian updating is supported or rejected by the data. In the Bayesian model, a subject with a type θ observes a signal x with probability induced by P_θ, and then computes the posterior given the signal, which we denote

$$m(\cdot|x) \in \Delta(\Theta, \mathcal{B}(\Theta)). \tag{A.1}$$

Let $S \equiv \{s^i : i = 1, \ldots, 5\}$ be the set of statements that the subject can make, where s^i is interpreted as *"I am in the i-th quintile"*. Given the signal x he has observed, the subject determines which of the five quintiles has the largest probability according to his posterior, that is, he solves:

$$\max_{i=1,\ldots,5} m(R^i|x), \tag{A.2}$$

and then states s^k if k is the solution of the problem (A.2).

Definition A.1. *A subject in the quintile R^i stating s^j is overconfident if $j>i$ and underconfident if $i>j$.*

The model implicitly describes a function giving for every θ a probability over the set of quintiles. Note that only we, the experimenters, observe θ, although with some noise due to the imprecision of the task.

An allocation function is a function $q:\Theta\to\Delta(S)$. An allocation function is induced by an experiment P with the distribution m over the type space Θ if it can be obtained from Bayesian updating according to P. Formally:

Definition A.2. *An allocation function q is induced by an experiment P with m the prior distribution over the type space Θ if there exists a choice function $C:X\to\Delta(S)$ such that*

$$\text{if } C(x,s^j)>0 \text{ then } m(R^j|x)=\max_k m(R^k|x), \tag{A.3}$$

and such that for every θ and s^j,

$$q_\theta(s^j)=\int_X P_\theta(dx)\,C(x,s^j), \tag{A.4}$$

We denote by $A(P)$ the set of allocation functions induced by an experiment P.

The allocation function of an experiment is not unique because the choice function C is not unique. Note that $(S,\mathcal{P}(S),(q_\theta)_{\theta\in\Theta})$, where $\mathcal{P}(S)$ is the set of all the subsets of S, is an experiment on Θ, dominated by P in the Blackwell order, since it is obtained from P though the Markov kernel C. The function q depends on the experiment P (and is a coarsening of P): we may use the notation q^P when we want to emphasize this dependence.

We denote $X^i\equiv\{x:\ \text{argmax}_j m(R^j|x)=i\}$. We can also define the average theoretical allocation function

$$A_q(R^i,s^j)=\int_{R^i} q_\theta(s^j)dm(\theta). \tag{A.5}$$

An allocation function displays overconfidence (respectively, underconfidence) at $\theta\in R^i$ if $q_\theta(s^j)>0$ for $j>i$ (respectively, $j<i$).

For our intended application, providing a test of the Bayesian model in our experimental data, a finite type space is enough. We consider a type space where a quintile coincides with a type. An individual has type θ^i if his IQ score in the Raven's matrices task is in the i-th quintile. So formally we have:

$$\Theta\equiv\{\theta^i:i=1,\ldots,5\}. \tag{A.6}$$

From the point of view of our more general model with a continuum of types, this simplification ignores the problem of aggregation of the different types within a quintile and simply assumes that all the individuals in a quintile are identical. We lose some information (e.g., it seem natural that people with higher IQ score have more optimistic beliefs that those with lower score in the same quintile), but we gain in simplicity in the analysis of the data.

A.1. *Experiments and allocation functions*

To make the search for the experiment P more systematic we may proceed as follows. First we pose the problem: in our simple environment (with finite types, signals and states), when can an observed empirical allocation function possibly be produced as the allocation function of some experiment, when the prior is uniform over the types? The answer turns out to be simple: if and only if each quintile considers itself more likely than any other quintile does. Formally:

Theorem A.3. *Let q be an allocation function. The following conditions are equivalent:*

1. *There exists an experiment $(X,\mathcal{X},(P_\theta)_{\theta\in\Theta})$ over some signal space X such that q is one of its allocation functions;*
2. *For every i*

$$q_{\theta^i}(s^i)=\max_k q_{\theta^k}(s^i). \tag{A.7}$$

Proof Let $(X,\mathcal{X},(P_\theta)_{(\theta\in\Theta)})$ be the experiment and C the choice function inducing q. Then for every i,

$$q_{\theta^i}(s^i)=\int_X P_{\theta^i}(dx)C(x,s^i).$$

By the definition of choice function, if $C(x,s^i)>0$ then

$$m(R^i|x)=\max_k m(R^k|x). \tag{A.8}$$

But in the present case $R^k=\{\theta^k\}$, and the m is uniform, so A.8 is equivalent to

$$P_{\theta^i}(x)=\max_k P_{\theta^k}(x), \tag{A.9}$$

and therefore for every k:

$$\begin{aligned} q_{\theta^i}(s^i) &= \int_{\{x:C(x,s^i)>0\}} P_{\theta^i}(dx)C(x,s^i) \\ &\geq \int_{\{x:C(x,s^i)>0\}} P_{\theta^k}(dx)C(x,s^i) \\ &\equiv q_{\theta^k}(s^i). \end{aligned}$$

Conversely, let q be an allocation function that satisfies (A.7). We construct an experiment inducing q as its allocations function. Let $X=S$, and for every i and j let $P_{\theta^i}(s^j)=q_{\theta^i}(s^j)$. This is an experiment: we only need to construct a choice function for this experiment that induces q. Let $C(s,s^j)=\delta_s(s^j)$ (*i.e.*, = 1 if and only if $s=s^j$ and = 0 otherwise). The condition (A.3) on the choice function follows from the assumption (A.7), and the induced allocation is $\sum_s q_{\theta^i}(s)\delta_s(s^j)=q_{\theta^i}(s^j)$. ‖

A.2. *MPQ questions*

We report here the questions in the *MPQ* for the two traits of Social Potency (Table A1) and Stress Reaction (Table A2).

Acknowledgments. The authors (who are listed alphabetically) gratefully acknowledge generous financial support for the Truckers and Turnover Project from the John D. and Catherine T. MacArthur Foundation's Research Network

TABLE A1
Social Potency

(1)	I am quite effective at talking people into things.
(2)	I am quite good at convincing others to see things my way.
(3)	I am very good at influencing people.
(4)	I do not like to be the centre of attention on social occasions.
(5)	I do not like to organize other people's activities.
(6)	I do not enjoy trying to convince people of something.
(7)	I enjoy being in the spotlight.
(8)	I perform for an audience whenever I can.
(9)	I usually do not like to be a "follower."
(10)	In most social situations I like to have someone else take the lead.
(11)	In social situations I usually allow others to dominate the conversation.
(12)	People find me forceful.
(13)	When I work with others I like to take charge.
(14)	When it is time to make decisions, others usually turn to me.

TABLE A2
Stress Reaction

(1)	I am often nervous for no reason.
(2)	I am often troubled by guilt feelings.
(3)	I am too sensitive for my own good.
(4)	I often find myself worrying about something.
(5)	I often lose sleep over my worries.
(6)	I sometimes get very upset and tense as I think of the day's events.
(7)	I suffer from nervousness.
(8)	If I have a humiliating experience I get over it very quickly.
(9)	My feelings are hurt rather easily.
(10)	There are days when I am "on edge" all of the time.
(11)	Minor setbacks sometimes irritate me too much.
(12)	My mood often goes up and down.
(13)	My mood sometimes changes from happy to sad, or sad to happy, without good reason.
(14)	Occasionally I have strong feelings (like anxiety or anger) without really knowing why.
(15)	Often I get irritated at little annoyances.

on the Nature and Origin of Preferences, the Alfred P. Sloan Foundation, the Trucking Industry Program at the Georgia Institute of Technology, the University of Minnesota, Morris, and the Federal Reserve Bank of Boston, and both financial and in-kind support from the cooperating motor carrier, its staff, and its executives. The views expressed are those of the authors, and do not necessarily reflect the views of any of their employers or of the project's funders. Carpenter and Rustichini also thank the NSF (grants SES-0617778 and SES-0924896, respectively).

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