Referee Report for the Paper
A Bias of Screening

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I. Summary

There are a lot of situations in real life where decision maker set a screen based on their own noisy unbiased assessments to help them make decision. A classic example is Ph.D. admission process, the admission committee can evaluate all applicants and give them grades with noisy bias. Committee can set a grade bar and admit those students with higher grade than this bar. This method is simple and intuitive, however, this method is not always optimal. It may not only reduce the number of accepted students, but also reduce their average expected grade.

The first example author issue is peer-reviewed academic publishing. This process is similar with what I talked in the admission situation. Each paper is valuated with some unbiased noise. If we choose the top 5% in the rank to publish, we will find the real expected value is around B+ which is worse rather than choosing top 13% to publish. This screening bias indicates that though threshold strategies are commonly used in theory and in practice, it may not be optimal way to make decision.

Then the author makes some basic assumptions and notions. We will follow his notions: V is impact variable, N is an unbiased random variable and editor uses the noisy evaluation $V + N$ to perform a screening. Setting b as the threshold, editor only publish those papers higher than b. And editor's goal is maximizing $\pi(b) = E[V|V + N \geq b]$. Following the basic setting, the author defines ***screening bias*** and ***extreme screening bias.*** In simple terms, an impact variable has no screening biases if $\pi(b)$ doesn't decrease as b increases. These biases are extreme if one can generate an almost optimal screening with a lower threshold.

In the section II.A, author proves that screening biases always exist, which is *Theorem 1:* ***Every bounded impact variable has extreme screening biases.*** During the proof of this theorem, some useful conclusions are interested: one is that even mild noises instigate biases, another is that we always construct screening biases shown as *Claim 1:* ***Every impact variable has a continuous noise variable that produces screening biases.*** The author confirms again that even the decision maker can have a very accurate screening system, *s.t* errors are mild in terms of magnitude and plausibility, biases still exist. Then author talks a weaker situation where probability distribution is finitely discrete, he proves that biases exist as long as the noise is not completely negligible relative to the impact variable. He defines ***V-distinguishable***, and proves *Claim 2:* ***For every finitely supported impact and noise variables where the noise is V-distinguishable, there exists*** $\boldsymbol{\alpha \in (0,1)}$ ***s.t*** $\boldsymbol{\alpha N}$ ***produces screening biases.*** The range of α also explains a same conclusion he talked that high-magnitude noise is not a necessary condition for a screening bias. Besides, he generalizes *Lemma 1* which shows that biases are likely to emerge at a top-level screening rather that a lower one. The leading conclusion is that designers should not concern themselves with biases whenever screening is restricted to low-level elements and when the potential loss from a limited noise is negligible. Author also states the property of ***Monotone Likelihood Ratio Property (MLRP).*** And this property will characterize optimal threshold strategies in Section III.

In the section II.B, author lists some implications of screening biases and explain its principle. The first implication is *Credit Ratings,* from what he talked before, a stricter loan conditions generate lower expected return but also make it riskier. Increasing the threshold will cause lose-lose situation. The second implication is *Auctions and the Winner's Curse*, the conclusion is similar. Higher open bid is not necessarily productive and does not guarantee efficiency. The third implication is *General Trade,* conclusion is that higher price may reduce the expected quality of products in the market by introducing relatively more low-value products with overzealous sellers.

In section III, author starts to talk some situations where threshold strategies are indeed optimal strategy. He proves *Theorem 2* which says threshold is an optimal strategy for every increasing and concave utility function if and only if for every two positive-probability sets A and B s.t A is above B and the first-order stochastic-dominance holds. So right now, he proves that threshold strategies are indeed optimal for some utility functions.

In section III.B, the author uses 2 examples, one is *The Peter Principle,* this example illustrates how suboptimal threshold strategies generate a bias that optimal non-threshold policies can overcome. Another is *Affirmative Action,* the conclusion is similar, the non-threshold strategy targets individuals with different noise realizations.

The last part is conclusion. There are two parts construct this paper. The first part he establishes the existence and robustness of screening biases, the second part he characterizes optimal threshold strategies.

II. Evaluation

The author proves a few important theorems. In real life, people's impact variable is usually bounded, people prefer to use a discrete number or an interval to evaluate something. In such situation, he finds extreme screening biases always exist. Then people will concern whether it is caused by high-magnitude noise? The author solves this question during the proof of *Claim 1*, he finds even the decision maker's estimation is very accurate which means the errors are mild in terms of magnitude. *Claim 2* continually indicates it. If we come back to real life, we should realize that even we improve our estimation system very well, we still meet the screening bias once it is not totally accurate.

Fortunately, author gives a possible way to decrease the screening biases. *Lemma 1* is a method to decrease the screening bias. If we insist using a threshold as the criteria, we should restrict to low-level elements, then the potential loss from a limited noise is negligible.

And those 3 examples author uses are also important. The author explains why in our real life, sometimes setting a high threshold will not lead to efficiency.

But author does not stop here, he also discusses the condition to make threshold strategy become optimal strategy. He uses stochastic-dominance property to find the condition of utility function such that decision maker can use threshold method to lead optimization.

This paper has a clear process to talk whether threshold strategy can lead screening bias or lead optimal strategy. It also explains some phenomenon that threshold does not work well in real life. So I personally think the paper works well, the main theorems and claims are robust.

III. Comment

The author could probably try to work on the following problems in the future. But of course, adding these assumptions may lead different results but more useful in real life.

C.1 Bias are not independent

In the example of peer-reviewed paper, the assumption is that N is symmetrically distributed and independent of V. I'm considering whether the author can generalize the model in the situation where ***N is not symmetrical and dependent of V.*** Because it often happens in real life, the editor may overvalue the high-quality paper, undervalue the low-quality paper and value neutrally the medium-quality paper. I understand change the dependency assumption may lead those theorems incorrect, but I will be happy if the author can talk which theorems are still true under this dependence situation.

C.2 Extend impact variable to unbounded variable

In the paper, author assume the ***valuation system is finite or bounded***, that's reasonable because people prefer to use discrete grade to do an evaluation. However, this discrete grade causes the screening biases, what if our valuation system is a continuous distribution? In this situation, the impact variable is not bounded and the support of the distribution is not finite. A natural question is that can we eliminate the screening bias? I'm looking forward the author can have some results about this guess.

C.3 Find the optimal threshold setting

If one person insists using the threshold strategy, how can he find the optimal threshold setting such that the conditional expectation is maximum? I wish the author can extend the *Theorem 2* to prove that we can always use some methods to find this threshold which is the best compared with other threshold.

References

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