Climate Prediction Markets and Convergence of Predictive Models

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Abstract

We present an agent-based model of a climate prediction market in which traders adapt their belief about the climate based on the monetary performance of their neighboring traders in a social network. We analyze the model to determine how a variety of factors affect whether climate prediction markets foster a convergence of market participants' beliefs regarding a true model of the earth's climate. We find that only the imposed "true model" itself significantly affects the convergence of beliefs. If the true model from which the temperature data is generated is auto-regressive, with no human-induced effects, participation in the prediction market, on average, does not cause convergence of traders' beliefs. On other hand, if anthropogenic climate change is real, traders' beliefs are more likely than not to converge toward the correct climate model due to participation in the market.

Introduction

The previous two decades saw a strong polarization of the climate change debate. Although the scientific consensus on the anthropogenic nature of climate change strongly increased, the average belief about anthropogenic climate change did not evolve much within the public [18]. In addition, the divide on anthropogenic climate change between liberals and conservatives has grown steadily, indicating that the question is becoming increasingly politicized and potentially disconnected from scientific evidence. This is troubling given the costs of a misinformed climate policy. If anthropocentric climate change is a myth but is taken to be true, a tremendous amount of public resources will be wasted on adaptation and mitigation efforts. On the other hand, if climate change is human induced but not recognized as so, the costs of inaction would be huge. Given that effective climate policies require long-lasting measures to be taken, the importance of an accurate consensus on the issue is manifest.

Attempts to foster such consensus face many social and psychological challenges. Recently, people have argued that such challenges could be met by setting up climate prediction markets [8, 18]. The idea of using prediction markets to efficiently aggregate information about uncertain events has been discussed for decades [7]. Prediction markets have been shown to have interesting theoretical properties [15, 4] and to perform well in terms of prediction accuracy in experiments [5, 6], agent-based models (ABM) [10, 9], and in the real-world [19].

However, to the best of our knowledge, the idea that prediction markets can generate consensus *on the factors* affecting uncertain events has never been quantitatively explored. ABMs of prediction markets have been studied [10, 17, 9], some of which feature communication between agents. In these models, however, beliefs about the uncertain outcomes are constructed in rather abstract ways. In particular, beliefs are not based on structural models from which agents could derive causal implications, and therefore these models are not suitable for investigating the convergence of the underlying explanatory models agents employ for prediction.

From a public policy perspective, changing the explanatory models of market participants is one of the most important roles that prediction markets might play.[1] Effective climate policy not only requires an accurate consensus on future climate *outcomes*. It also requires an accurate consensus on the causal *mechanisms* influencing such outcomes. If people agree that temperature will rise, but some believe it will be due to greenhouse gases, while others believe that it will be caused by increased solar activity, inconsistent and ineffective policies may be implemented. Our model is designed to investigate whether, and under what conditions, prediction markets can foster such convergence in predictive models.

Model Design

TODO: Martin use this text below (it is commented out) from the original document and flesh it out for the Supplementary Material and then write a couple paragraph summary and the key equations to put in this main article right here.

In particular, lets go over main design and then define what each of these mean in our model:

- `ideo` $\sim Unif(0,1)$
- `market.complet` $\sim Unif(0,1000)$ (mapped into integer)
- `n.edge` $\sim Unif(100,200)$ (mapped into integer)
- `n.traders` $\sim Unif(50,250)$ (mapped into integer)
- `risk.tak` $\sim Unif(0,1)$

[1] and perhaps the most important potential social benefit of prediction markets given the comparable predictive power of statistical models, which are less expensive than setting up and maintaining prediction markets [3].

- `seg` $\sim Unif(0,1)$
- `true.model` $\sim Binom(0.5)$

Model Analysis

We estimated the effects of the parameters of our model on the difference between the fraction of traders who believe in the true model at the beginning of the experiment and the fraction who believe in the true model at the end of all trading sequences. The sensitivity analysis is based on a Latin Hypercube Sampling of 10,000 parameter sets from the following distributions [1, 2].

- `ideo` $\sim Unif(0,1)$
- `market.complet` $\sim Unif(0,1000)$ (mapped into integer)
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- `risk.tak` $\sim Unif(0,1)$
- `seg` $\sim Unif(0,1)$
- `true.model` $\sim Binom(0.5)$

We use the model to simulate 10,000 outcomes based on the input paramter sets and then conduct a partial rank correlation coefficient analysis on the relationship between the input matrix, X, resulting simulated vector, y [11, 12, 14]. Partial correlation computes the linear relationship between the part of the variation of X_i and y that are linearly independent of other X_j $(j \neq i)$. The only difference with the partial correlation and partial *rank* correlation (which we use here), is that the outcome variable y is first ranked-transformed in order to allow us capture potentially non-linear relationships.[2]

Our sensitivity analysis, illustrated by Fig. 1, strongly suggests that the magnitude of convergence to the true model is conditional on what the true model actually is: if anthropogenic climate change is true, a prediction market is likely to cause convergence to the true model; while if anthropogenic climate change is false, and the model of the climate is in fact auto-regressive, convergence to this true model is unlikely (Fig. 2).

[2]That is every value, y_s, in the data set is replace by a number $f(y_s) \equiv |\{y_r \mid y_s > y_r\}|$, where y_r are the other observed values of y in the data set.

Discussion

Proponents of climate prediction markets argue that climate prediction markets will foster convergence to the best approximate model, whatever the actual true model is. It is framed as an apartisan proposal: if climate change is not anthropogenic, traders will converge to non-anthropogenic beliefs similar to how they would converge to anthropogenic beliefs if the climate is truly influenced by human activities. Our findings contradict this assumption.

TODO: Jonathan, perhaps talk about the policy implications of this finding...

Acknowledgements

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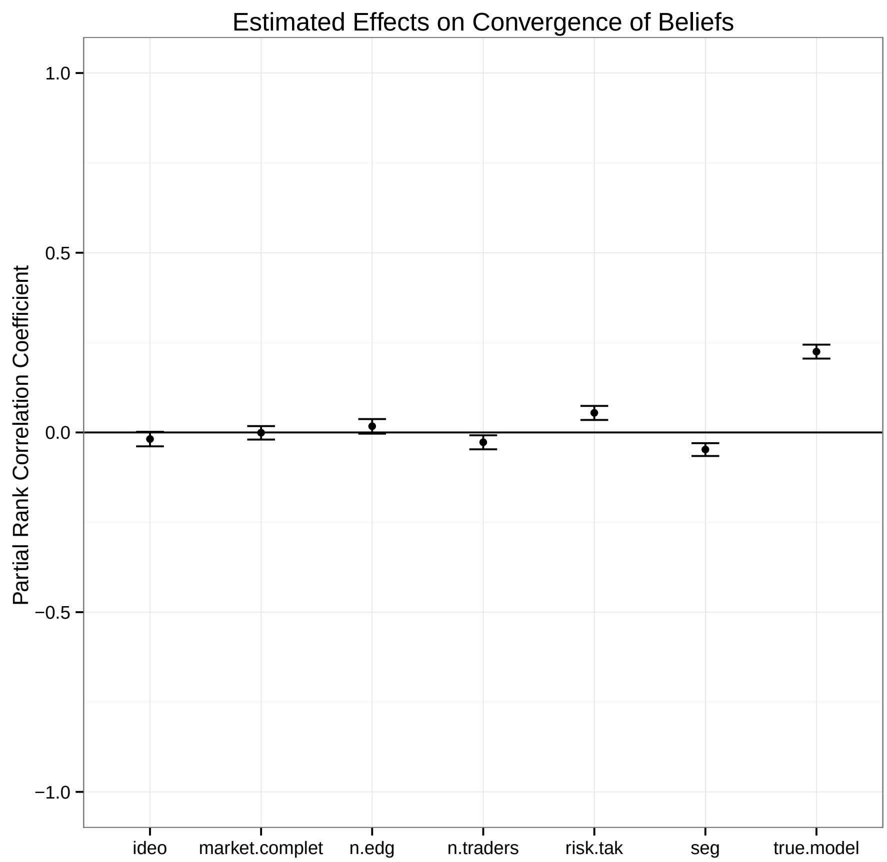

Figure 1: Partial rank correlation coefficient analysis based on 10,000 simulated parameter sets [12, 14] of the effects of ideology, market completeness, number of edges in social network, number of traders in market, risk taking propensities, segregation measure of the social network, and the true climate model on the convergence of traders' beliefs. Lines are bootstrapped 95% confidence intervals.

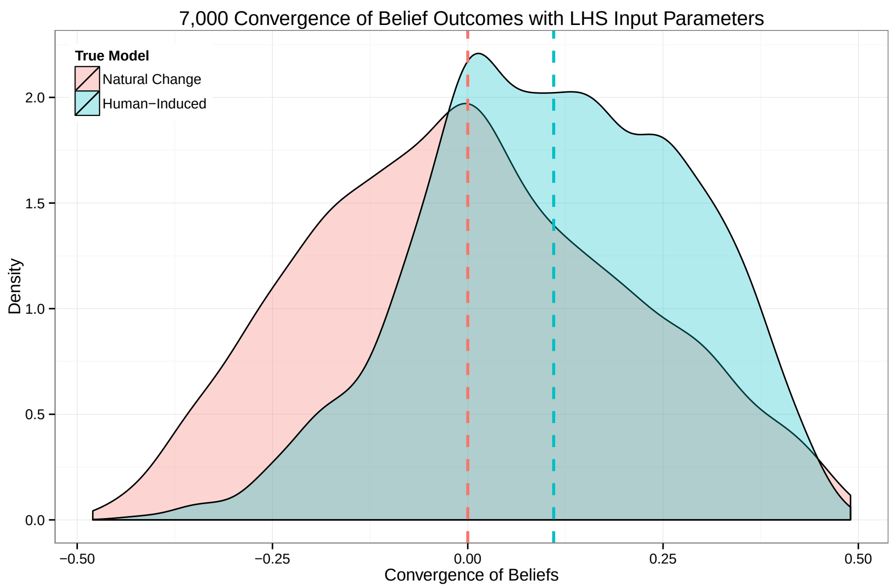

Figure 2: Density of 7,000 convergence of belief model outcomes with 7,000 Latin Hypercube Sampled input parameter sets. 3,500 of the Latin Hypercube Sampled input parameter sets have "human-induced" climate change as the true model and 3,500 have "natural change" climate change as the true model. Dashed lines are the medians of the two densities (0, 0.11). Possible values of convergence of beliefs range from -1 to 1.

Figure 3: Temporal evolution of convergence of beliefs.