Betting and Belief: Prediction Markets and Attribution of Climate Change

John J. Nay, Martin Van der Linden, Jonathan Gilligan

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Abstract

We present a simulation model as a computational test-bed for climate prediction markets. Traders adapt their beliefs about future temperatures based on the monetary performance of their neighboring traders in a social network. We conduct experiments with the model to determine how a variety of social factors and the temperature data-generating process may affect the extent to which climate prediction markets foster a convergence of market participants' beliefs regarding a true model of the global climate. We simulate two alternative climate futures: one where the natural log of CO_2 is the primary driver of global temperature and one where sun spots are the primary driver. These represent the two most plausible competing views. Market participation causes most traders to converge toward believing the "true" climate model in a relatively small number of years, suggesting that a climate market could be useful. (150 word limit)

1. Introduction

The climate change debate has become strongly polarized over the past two decades. Although the scientific consensus on the anthropogenic nature of climate change strongly increased, beliefs about climate change did not evolve much within the public (Vandenbergh, Toner, and Gilligan 2013). In addition, the divide on anthropogenic climate change between liberals and conservatives has grown steadily as the question is becoming increasingly politicized and potentially disconnected from scientific evidence. The costs of misinformed climate policies are high. If climate change is not human-induced but is believed to be so, public resources will be spent on unnecessary efforts. On the other hand, if climate change is human-induced but not recognized as so, the costs of inaction could be devastating. 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, some of which could be adressed by creating climate prediction markets where participants can "put their money where their mouths are" (Hsu 2011; Vandenbergh, Toner, and Gilligan 2013). The idea of using prediction markets to efficiently aggregate information about uncertain event outcomes has been widely discussed (Horn et al. 2014). Prediction markets have interesting theoretical properties (Set and Selten 1998; Hanson 2012), and perform well in terms of prediction accuracy and information aggregation in experiments (Hanson, Oprea, and Porter 2006; Healy et al. 2010) simulation models (Klingert and Meyer 2012; Jumadinova and Dasgupta 2011) and the real-world (Wolfers and Zitzewitz 2006; Pathak, Rothschild, and Dudik 2015). Prediction markets have been shown to be effective at identifying which scientific publications are likely to be successfully replicated (Dreber et al. 2015).

Bloch, Annan and Bowles (2010) have proposed using derivatives markets to reduce the scientific uncertainty in estimating the impact of future climate change. Existing prediction markets (e.g. hypermind.com, betfair.com, and predictit.org) focus on near term events such as elections months away, so it is difficult to extrapolate empirical findings to the climate case. Furthermore, we are interested in investigating the unobservable beliefs of traders. Therefore, we turn to simulation modeling informed by climate and economic theory. We simulate a prediction market where traders exchange securities related to climate outcomes to explore whether, and under what social and climate conditions, prediction markets may be useful for increasing convergence of climate beliefs. Our work can be extended as part of a computational design process for effective climate prediction markets.

2. Related Work

Tseng et al. (2010) create an agent-based model (ABM) of a continuous double auction market with multiple market strategies, including two variants of the zero-intelligence agent. They compare the behavior of their simulation with data from a prediction market for the outcome of political elections. They find that despite their simplicity, zero-intelligence agents capture some salient features of real market data. Klingert and Meyer (2012) reach similar conclusions with respect to experimental data from Hanson, Oprea, and Porter (2006). In their simulation, Klingert and Meyer (2012) compare continuous double auctions with logarithmic market scoring rules and find that the latter generally outperform continuous double auctions in terms of prediction accuracy. In some variants of the two last models, agents' strategies feature learning, but these are rather basic and unrelated to a formal predictive model.

Jumadinova and Dasgupta (2011) conducted research similar to ours, as they explicitly include information about uncertain events in their model. Jumadinova and Dasgupta (2011) study a continuous double auction model in which agents update their beliefs about uncertain events based on information on the event. New beliefs are modeled as a weighted sum of the last period's beliefs and market prices. The agents' information set changes every period. The better the information set, the more likely the agent is to put higher weight on last period's prices when revising their beliefs. Little structure is imposed on the information set and the way it is used to generate the weights in the update function. Therefore, the model does not allow for investigating the convergence of predictive models. Ontañón and Plaza (2009) study the effect of deliberation on a simulated prediction market. They assume that agents use Case-Based Reasoning (Aamodt and Plaza 1994) to debate uncertain outcomes with their neighbors in a social network. Although the model could in theory be used to assess convergence of predictive models by looking at the arguments agents adopt after the deliberation, this is not done by the authors. Also, the way beliefs are formed and revised through argumentation is too abstract for studying climate prediction markets, where beliefs should be based on statistical time series models.

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 (Klingert and Meyer 2012; Tseng et al. 2010; Jumadinova and Dasgupta 2011), 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. This is perhaps the most important social benefit of prediction markets given the comparable predictive power of statistical supervised learning models, which can provide information at a much lower cost than creating and maintaining a market (Goel et al. 2010). 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.

2. Model Design

Traders bet on global temperature anomalies six years in the future. During the six-year period, traders buy and sell futures. Every year, traders update their models and forecast of future temperatures based on newly available data. At the end of each six-year period, winners collect gains and traders revise beliefs about climate models, based on their ideology and the beliefs of top earners in their social network. In this section, we describe the models used to generate future temperature data, agents beliefs about those models, the market procedures, and the social network connecting agents. We conclude with details on model dynamics and an overview of the model parameters we experimentally vary.

Temperature Models

For climate time-series, we use the annual anomaly of global mean temperature. For years from 1880–2014 we use the GISTEMP global mean land-sea annual temperature anomalies (GISTEMP Team 2016; Hansen et al. 2010) and for years from 2015 onward, we project future climates under two alternative theories: In both theories, changes in global temperature are proportional to changes in a deterministic forcing plus a stochastic noise term. For simplicity, we choose two alternative expressions for the deterministic climate forcing: one, which corresponds to conventional climate science, takes the natural logarithm of the atmospheric carbon dioxide concentration in parts per million (Archer 2012, 37), and the other, which corresponds to an alternative theory advocated by many who doubt or reject conventional climate science, takes the total solar irradiance (the brightness of sunlight, in Watts per square meter, at the top of the atmosphere) averaged over the 11-year sunspot cycle (Soon 2005). Most scientific models of the earth's climate include many forcings, including carbon dioxide, other greenhouse gases, aerosols, total solar irradiance, and more. In these models, the changing CO_2 concentration is, by a large margin, the strongest forcing (IPCC 2013, 14), so for simplicity we take this as the model. Choosing only one forcing term for each of the competing models simplifies comparison because each has the same number of adjustable parameters.

For CO_2 we used historical emissions through 2005, harmonized with RCP 8.5 representative concentration pathway from 2005 onward (Kolp and Riahi 2009; Riahi et al. 2011) and for TSI we used the harmonized historical values, with a projection through 2100 from Velasco-Herrera *et al.* (2015), which seems to be the best TSI model.

Warming coefficients for each model were determined by linear regression of historical temperatures from 1880–2014 against the historical values for each model's forcing term. The noise model was determined by fitting an ARMA(p, q) model to the residuals from the regression for all combinations of $p, q \in [0, 1, 2]$ and using the Watanabe-Akaike Information Criterion to select the optimal model (Vehtari, Gelman, and Gabry 2015). The optimal model in both cases was AR(1).

Future climates were generated by multiplying the warming coefficients for each model for warming coefficients adding stochastic AR(1) noise to deterministic warming using parameters fit to the historical data (1880–2014). One realization of future climates for both the $\ln(CO_2)$ and TSI models is shown in Fig. 1.

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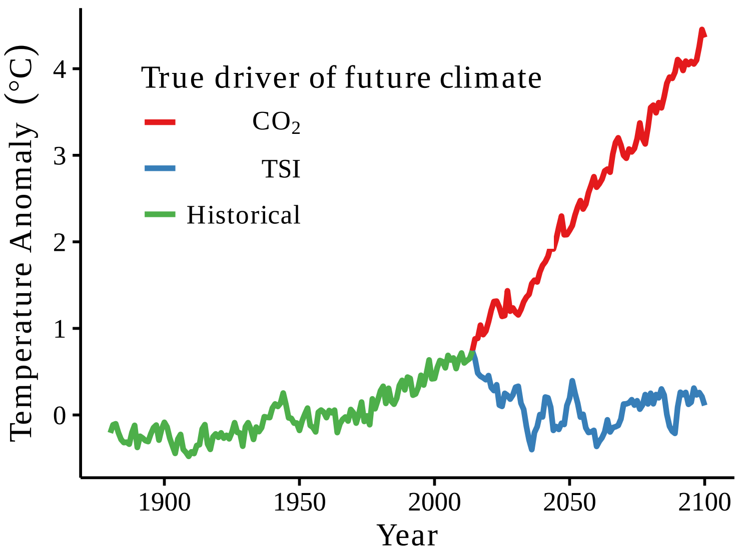


Fig. 1. Historical measurements of temperature and temperature futures in two alternate realities.

Climate Beliefs

Traders use one of the two models (temperature depends on CO_2 or TSI) to forecast future temperature. These models are interpreted as the trader's beliefs about the true climate process, the driving factor of long-term global temperatures. They represent pervasive positions on climate change in the public debate. In order to approximatively match the current configuration of beliefs in climate change in the United States, the CO_2 model is randomly assigned to half of the traders, while the TSI model is assigned to the other half of the traders.

Thus, both when the true data generating process is CO_2 and TSI, approximately half of the traders use the true data-generating model to make predictions. Traders using the true model do not necessarily make perfectly accurate predictions however. Although these traders believe in the correct *functional form* of the model, they still need to calibrate their model based on limited noisy data. Therefore, the values these traders assign to the parameters of the model will typically be different from the exact parameters in the data-generating process.

Jonathan, can you describe the model estimation process here?

Traders and Market

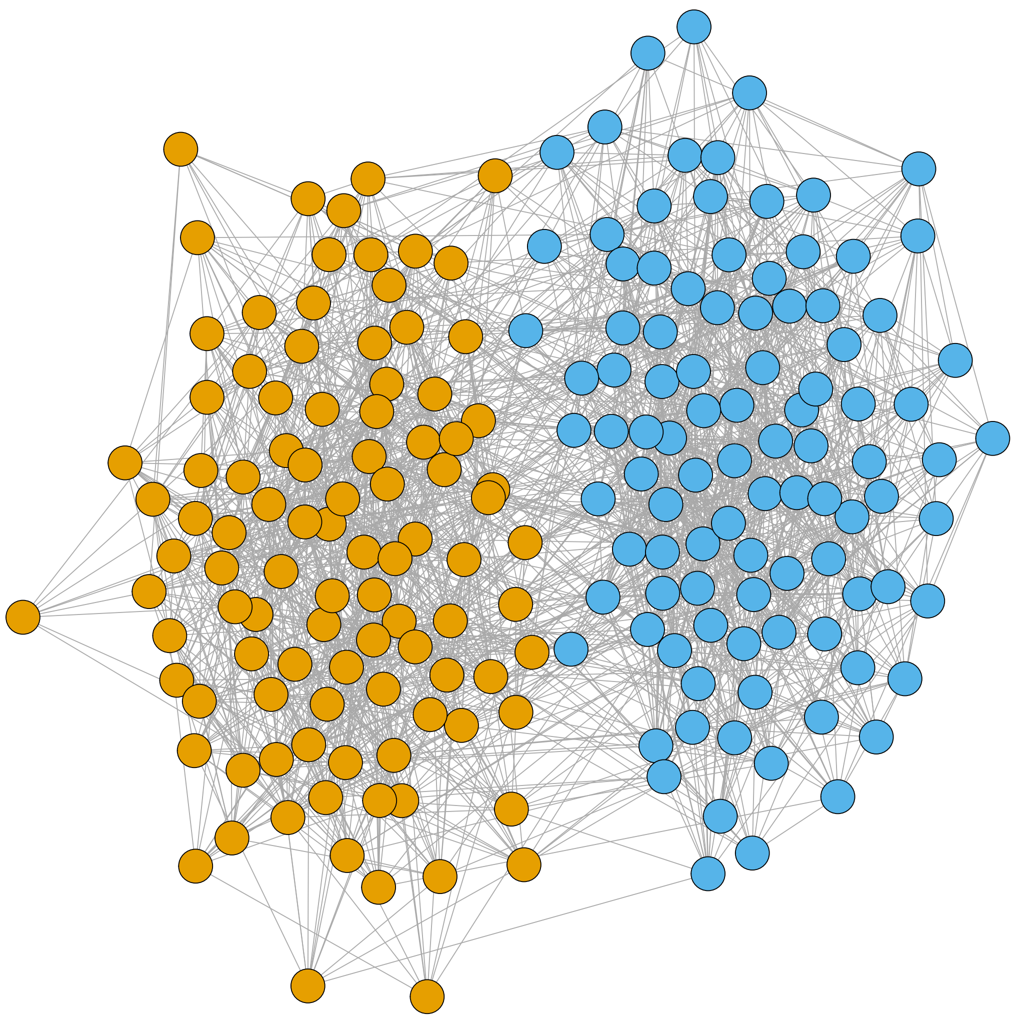
Traders are initially endowed with a single experimental currency unit (ECU). Traders use their model to forecast the distribution of future temperature and determine their reservation price for different securities. Each security pays 1 ECU at the end of the trading sequence if the temperature at the end of the sequence falls into a certain range. Traders are risk-neutral expected utility maximizers. Therefore, their reservation price for a security is simply their assessment of the probability that the temperature will fall in the range covered by the security at the end of the sequence.

Based on their reservation price, agents behave as "zero-intelligence" traders (Gode and Sunder 1993). They attempt to sell securities at a random price above their reservation, and to buy securities at a random price below their reservation. These trading strategies are simple but provide accurate approximations of behavior in prediction markets (Klingert and Meyer 2012), and in financial markets more broadly.

Based on traders' sell and buy orders, traders exchange securities following a continuous-double auctions (CDA) procedure (see Model Dynamics below for more details). CDAs or some close variants are common procedures to match buy and sell orders. CDA are notably used on large stock markets (Tseng et al. 2010).

Social Network

Traders are part of a social network where each agent forms two links at random, and then forms links randomly, ensuring that each agent is connected to at least two other agents. Every time securities are realized, each trader looks at the performance of her richest neighbor in the network. Traders start with the same initial amount of ECU and differences in ECU can only come from market interactions. Therefore, if some trader is poorer that her richest neighbor, the trader interprets this as an signal that her richest neighbor may have a better model of the climate. Then, the trader considers adopting the model of her richest neighbor. For each trader, the willingness to revise her belief is determined by how ideologically loaded her belief is, which is a parameter we vary in our experiments.



An example of a snapshot of a social network is depicted in Figure X. We assume that the initial network is segregated: traders who initially believe in CO_2 forcing (resp. TSI) are more likely to be linked with other traders who also believe in CO_2 (resp. TSI). This reflects reality where cultural and social groups are highly correlated with climate change beliefs. Although traders can change their approximate model over time, the connections between traders do not change as the market unfolds, i.e the edges are fixed.

Model Dynamics

The time periods t are grouped into trading *sequences*. In a given sequence, the potential payments associated with traded securities are all based on the temperature at the end of the sequence. For instance, the third trading sequence might start in period $t = 1964$ and end in period $t = 1970$. In this case, a security traded in the third sequence pays 1 ECU if the temperature at $t = 1970$ falls into the range of temperatures covered by the security.

At each time t, traders are assumed to know the past value of the temperature $T_{0:t}$, carbon dioxide $CO2_{0:t}$, and total solar irradiance $TSI_{0:t}$. In a sequence finishing at time t^*, traders also have common knowledge of $CO2_{t:t^*}$ and $TSI_{t:t^*}$, the future values of carbon dioxide and total solar irradiance up to t^*. However, at any t, traders do not know the value of any future temperatures. In particular, in a given sequence, traders do not know the value of T_{t^*}. Traders can only predict T_{t^*} using their approximate model and their knowledge of $T_{0:t}$, $CO2_{0:t^*}$, and $TSI_{0:t^*}$. Notice that because $T_{0:t}$, $CO2_{0:t^*}$, and $TSI_{0:t^*}$ are common knowledge, in each period t, any two trader with the same approximate model m forms the same stochastic beliefs about future temperatures $F_{tm}(T_{t^*} \mid T_{0:t}, CO2_{0:t^*}, TSI_{0:t^*})$.

At each time t, traders:

1. recalibrate their approximate model based on the new set of temperature data available at t,
2. compute their stochastic beliefs about future temperatures $F_{tm}(T_{t^*} \mid T_{0:t}, CO2_{0:t^*}, TSI_{0:t^*})$ and use it to determine the expected value they attached to each security, and
3. trade on the CDA market as follows:
   - Every trader i choses at random a security s_i^B she will try to buy.
   - Every trader i also chooses at random a security s_i^S she will try to sell among the securities she owns a positive amount of (if any).
   - Traders then decide of their selling price p_i^S and buying price p_i^B. To do so, traders first compute their expected values $E(s_i^B)$ and $E(s_i^S)$ for securities s_i^B and s_i^S. Then traders set p_i^S at random above $E(s_i^S)$ and p_i^B at random below $E(s_i^B)$ (see Model Parameters below for more details).
   - Traders go to the market one at the time, in an order drawn randomly for each t.
   - When trader i comes to the market, she places limit orders in the order book. These orders specify that i is willing to buy s_i^B at any price below p_i^B, and to sell s_i^S at any price above p_i^S.
   - The market maker then tries to match i's orders with some order which was put in the book before i came to the market.
   - If there are outstanding sell offers for s_i^B at a price below p_i^B, a trade is concluded. Trader i buys one unit of s_i^B from the sellers who sells at the highest price below p_i^B, and the sell and buy offers are removed from the order book.
   - If there are outstanding buy offers for s_i^S at price above p_i^S, a trade is concluded. Trader i sells one unit to the buyer who buys at the highest price above p_i^S, and the sell and buy offers are removed from the order book.
   - Whenever all traders have come to the market, any remaining outstanding offer is removed from the order book, and the trading period is concluded.

At t^*, when the sequence ends, there is only one security s^* associated with a range of temperatures including the actual temperature T_{t^*}. At t^*, traders:

1. receive 1 ECU per unit of s^* they own, and
2. consider adapting their neighbors' approximate model as described above.

Model Parameters

The model depends on the following parameters, which we vary in simulation experiments to determine their effects on the convergence of beliefs. We group the parameters into climate, network and individual behavioral factors.

- Climate parameters:
  - **true.model**: temperature data-generating process, CO_2 or TSI.
- Network parameters:
  - **n.traders**: the number of traders.
  - **n.edg**: the number of edges in the social network.
  - **seg**: the initial degree of homophily in the network. The higher **seg**, the higher the initial homophily.
- Behavioral parameters:
  - **risk.tak** : determines the distribution of risk-taking behavior. For each trader i, the level of $\texttt{risk.tak}_i$ is drawn uniformly at random from [0,`risk.tak`]. The higher $\texttt{risk.tak}_i$, the higher (resp. lower) the price i will set for the securities i tries to sell (resp. buy). Formally, let $\texttt{reserv}_{it}$ be the reservation price of trader i at time t for some security s. Then trader i picks her buying (resp. selling) price for s uniformly at random in the interval $[\texttt{reserv}_{it}, \texttt{reserv}_{it} * (1 - \texttt{risk.tak}_i)]$ (resp. $[\texttt{reserv}_{it}, \texttt{reserv}_{it} * (1 + \texttt{risk.tak}_i)]$).
  - **ideo** : determines the degree of "ideology" of traders. For each trader i, the level of $\texttt{ideo}_i$ is drawn uniformly at random from [0,`ideo`]. If ideo is high, traders will not revise their approximate models easily, even when faced with evidence that their richest neighbor is doing better than them. Formally, for each trader i and each sequence, a parameter d_i is drawn from $[0, \texttt{ideo}_i]$. The value of d_i is the probability that i adopts one of her neighbors' approximate model if this neighbor is doing better than i at the end of the sequence (in monetary terms).

3. Results

Historical Data

As a validation that the market is operating correctly, we run the market with actual temperatures 1880 to 2015 and market betting from 1931 to 2014. Before 1980 there is no statistically significant warming trend so we would not expect the market to change beliefs before then. As a global warming signal begins to show up in 1980s, traders begin to converge toward the $\log(CO_2)$ model (Fig. 2).

Future Scenarios

Our primary focus is on simulating the market in future scenarios. This is more relevant for policy design and more interesting theoretically due to the increasing divergence of global temperature values under the two future scenarios. The sensitivity analysis is based on a Latin Hypercube Sampling of parameter sets from the following distributions (Beachkofski and Grandhi 2002; Carnell 2012).

- 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 $\sim Unif(0, 1)$

- 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, and the resulting simulated outcome vector of belief convergence scores, y (Marino et al. 2008; Pujol et al. 2014; Saltelli, Chan, and Scott 2009). 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 the partial rank correlation that we use here is that the outcome variable y is first ranked-transformed in order to allow us capture potentially non-linear relationships. 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.

Our sensitivity analysis, Fig. 3, shows that ideology, risk tolerance, the number of traders, the number of edges per trader, the segmentation of the social network, and the true model all statistically significantly affect convergence. Segmented social networks can create an "echo-chamber" effect. Market participation causes traders to converge toward believing the "true" climate model; however, when the true model is CO_2-driven there is more convergence due to less noise in the relationship between predictor variable (log of CO_2 versus TSI) and temperature.

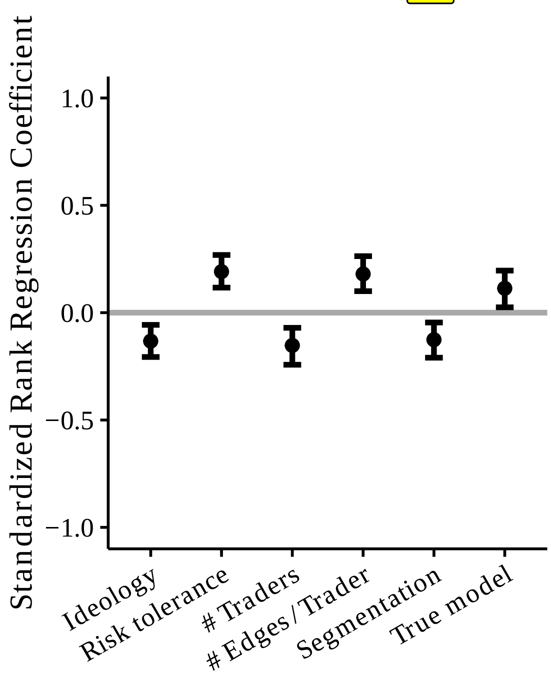


Fig. 3. Estimated effects of model parameters on convergence of beliefs in future scenario.

The sensitivity analysis averages over time and thus masks time trends. We randomly drew from the above distributions for ideology, risk tolerance, and the number of traders, and conducted an experiment crossing 95% and 5% percentile values for the number of edges per trader and the segmentation of the social network and both values for the true model. We then collected the time series of convergence across these eight designs for visualization of the distributions of convergence over time (Fig. 2). Under most parameterizations, within 15-20 years, the median percent of traders believing in the true model is over 75%.

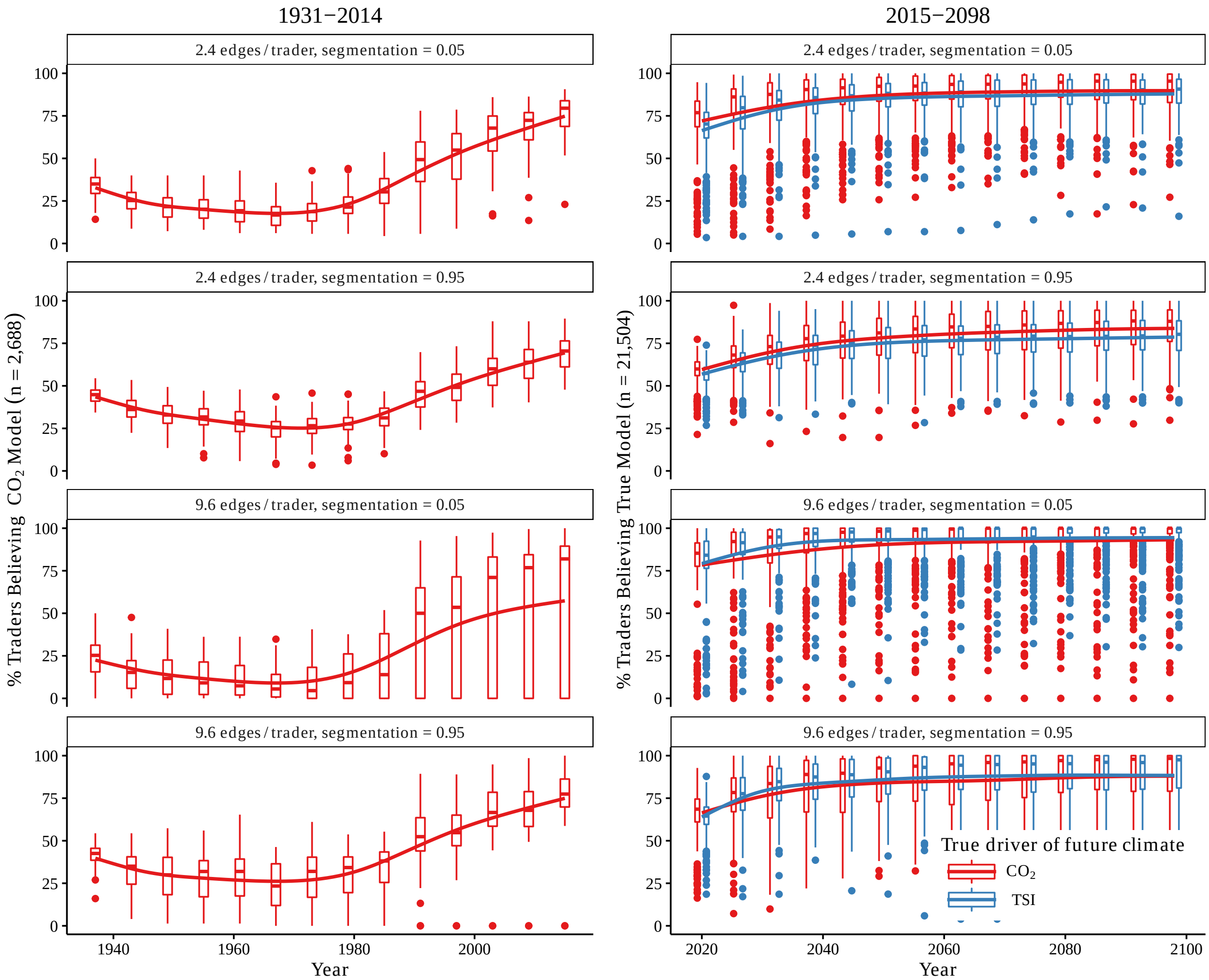


Fig. 2. Convergence over trading sequences.

4. Discussion

We simulate two alternative climate futures: one where the natural log of CO_2 is the primary driver of global temperature and one where sun spots are the primary driver. These represent the two most plausible competing views in the public discourse and our analysis is agnostic about which is "true". Market participation causes traders to converge toward believing the "true" climate model under a variety of model parameterizations in a relatively small number of years, suggesting that a climate prediction market could be useful regardless of which climate change beliefs ultimately turn out to be the best model of temperature change.

All code for the model is available at johnjnay.com/predictMarket. This project is a computational test-bed for public policy design: our code can be extended to test the effects that trading strategies, cognitive models, future climate scenarios, and market designs have on the evolution of trader beliefs.

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