Pricing ENSO Derivatives

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1 Core themes/ideas

1.1 Introduction

- Existing traded markets don't hedge climate risk directly
- Climate could be managed through non-traded markets (e.g. insurance) but there are utility to trading

1.2 Body

- Introduce a tool that is necessary but not sufficient to start the first direct climate markets
- Pricing financial products around uncertainty in climate forecasts
- Does information about ENSO change sufficiently to warrant trading?
- Considering modeling advantages and identification of mispricing
- Positive externality better climate models

2 Changes/Additions from dissertation chapter

- report bandwidth on kernel
- use MLE algorithm for fitting distributions (unless specific reason to do otherwise)
- motivation on normal
- consider using color gradient on the red and blue bands on the payout graph
- change the month scale (?)
- 3.11 consider rounding

- one st dev with number in parens
- move 3.14 up into distb section
- define neff and Rhat for tab 3.2
- can we say something about the the complexity of the problem and it's implication of the pricing?

3 Introduction

3.1 1 page summary of paper

3.2 Large unmanaged risk related to climate (status quo)

Climate risk is a growing concern for hedgers across the globe.

DISSREF estimates El Niño/La Niña's economic cost of this teleconnection, finding:

- ENSO risk is large enough in absolute terms to justify formal risk markets;
- large pools of ENSO risk offset one another in time and space, suggesting that ENSO markets could sustain balanced, direct trading among hedgers; and
- ENSO creates a pool of economic risk that is comparable to those underlying some large futures markets today.

3.3 Short-comings of existing schemes for managing climate risk

Yet, those hedgers have never had the opportunity to manage that risk on exchange traded derivatives markets.

3.3.1 Policy markets

There are markets covering the policy response to climate change, like those on emissions permits. But those markets focus on the policy response to climate change, not climate change per se. The EU's emissions-trading system (ETS), the legally binding system underpinning the largest carbon trading system on the planet, recently provided a jarring reminder of that distinction. On April 16, 2013 the European Parliament voted against proposals that would have altered the scheduled for issuing emissions permits under the ETS. That day, the price of EU carbon permits fell 40 percent [The Economist(2013)]. [ADD IN LINE ABOUT BASIS AND DEFINE BASIS]

3.3.2 Weather != climate

Of course, there are exchange-traded weather indexes. But it is difficult to see global scale changes in climate patterns just looking at the individual cities and regions those markets cover. Indeed, because those markets are so localized they miss the chance to attract liquidity from the diverse groups of hedgers that face dire consequences from changing weather patterns across the planet. That limited scale may explain some of their struggle to establish liquidity.

3.3.3 Climate linked business indexes

One possible alternative For example, the stocks price of reinsurers, companies with direct downside risk from extreme cliamte events, tend to be driven as much by their investing returns as by their climate linked losses[Kurtov(2010)].

3.4 Geophysical indexes as an atlernative

We need something actually linked to the climate.

An index where:

- The index has mmediate consequences
- Genuine uncertainty - Some risks too certain for hedging (rising sea levels)
- Error around estimates can be quantified (vs. IPCC, "very likely")
- Models verifiable

This rules out many geophysical indexes but...

Teleconnections Instead, there is a need for true climate markets. Teleconnections are great candidates to provide what existing markets don't. Example of what climate scientists call teleconnections. Teleconnections refer to the statistical and physical links between regional anomalies in the ocean and atmosphere and patterns of weather around the world.

El Niño/La Niña The most famous teleconnection involves El Niño/La Niña, a shift in ocean temperatures (and atmospheric pressure) in the Pacific Ocean that wreaks havoc on agricultural and energy markets and occasionally causes outright humanitarian crises in South America, Southeast Asia, and Australia.

El Niño is climate change as we experience it Nature paper on ENSO and climate change (there seems to be a link)

And it is big DISSREF Flood and epidemics on South America's Pacific Coast as discussed above South America hosts the most devastating impacts of the El Niño/La Niña. Based on my statistical analysis of disaster costs over the last half century, I estimate that an extreme El Niño (of which there have been 3 or 4 in the last century) causes median economic damages across the region of USD 3.4b.

Flooding in Pacific Asia and Oceania - This impact is generally associated with La Niña and has caused headline-grabbing destruction in recent years. I estimate that the expected impact of a La La Niña event of the same magnitude as that of 1988, (of which weve had two since 1970) causes regional damages of more more than USD8b in absolute damages. This may be an underestimate however, given that official Australian figures for the economic damage from the 2010 La Niña, which was not particularly catastrophic by historical standards, were roughly USD 12.5 billion.

Cite literature on El Niño and La Niña consequences (extra benefit is that much is in developing and emerging economies)

3.5 Introducing the potential for El Niño/La Niña

The best indicator that indexes of El Niño/La Niña are ready for exchange-trading is that one is already being used to settle a formal risk management.

In 2011, Caja Nuestra Gente, a large microfinance bank in Peru, purchased index-based insurance to protect its loan portfolio against defaults after catastrophic El Niño flooding. That insurance was developed by GlobalAgRisk, a research group led by University of Kentucky professor, Jerry Skees, with support from the Gates Foundation.

Ninety-five percent of the risk on the policy went to international reinsurer PartnerRe and five percent was held by the Peruvian insurer, La Positiva.

Payment on GlobalAgRisks El Niño insurance is based solely off the sea-surface temperature, as measured by the US's National Oceanic and Atmospheric Administration (NOAA) over defined regions off the coast of Peru. Sharp rises in that temperature, particularly in the months of November through January, define the El Niño phenomenon and are the cause of catastrophic flooding in Peru. (The opposite is true in La Niña years with the same index showing colder than normal temperatures which cause flooding on the other side of the Pacific in Australia and Southeast Asia.)

3.6 If we already have insurance, why do we need traded markets?

- Better for asymmetric information

  Does not require early closing date

  Can better integrate multiyear trends

  Can integrate information on climate change

- Provision of public information
- Maximiing welfare through lower cost of risk transfer

  Direct risk transfer

  Lower barriers to entry for motivated speculators

3.6.1 (Better for asymmetric information) Limitations of insurance

markets when forecasting is possible, closing windows will only get longer over time The biggest advantage of moving an El Niño/La Niña index to futures and options-on futures involves dynamic pricing of the underlying index. Currently, the sales closing date for the insurance is a full year before the period of coverage meaning that a firm looking for coverage during the 2013 El Niño season will need to choose whether or not to buy by then end of January 2013.

This schedule avoids the adverse selection problems created by El Niño forecasts, which are improving incrementally every year and open up the possibility of opportunistic purchases with the sophisticated buyers only buying coverage in years where they think an extreme El Niño is likely. Indeed, in the first year that GlobalAgRisks El Niño insurance was on sale, a large fishing company expressed interest in purchasing coverage, but requested additional time, beyond the original sales closing date, to make a final decision. In those critical weeks, new forecasts did come out suggesting El Niño was less likely. While it is difficult to directly link the fishing company's subsequent decision not to purchase coverage to those forecasts, the experience provided a stark reminder of the adverse selection problems inherent to insurance based on a forecast-able index. In the following year, the sales closing date was moved to January.

The lag between paying for and receiving coverage under GlobalAgRisks El Niño insurance increases the opportunity cost of hedging and means that the market is unlikely to attract the attention of risk managers with shorter planning horizons. These are problem that would be avoided altogether in exchange-traded markets, where prices are free to move as new forecast information becomes available.

3.6.2 (Provision of public information) Traded markets (securities or derivatives) would increase social gains by providing excellent forecasts

The knock-on effect of dynamic pricing would be better public and private decisions related to this key climate phenomenon. Exchange-traded El Niño/La Niña derivatives would provide public information not just about the price of risk protection but also about the likelihood of extreme El Niño/La Niña events. Currently decision makers (particularly in Peru) have to grapple with many competing El Niño/La Niña forecasts, often built using different datasets and methodologies.

International Research Institutes for Climate and Society run by Columbia University and NOAA provides a running tally of the forecasts of the best El

Niño/La Niña models from academia and national meteorological services. One look at that graph makes clear the need for the definitive consensus forecast that derivatives markets would provide. Without that touchstone newspapers and politicians in the most effected countries (Peru and Australia in particular) have often leaned heavily on alarmist forecasts - creating El Niño fatigue among ordinary citizens and policy makers.

3.6.3 (Maximing welfare through lower cost of risk transfer) Two-sided markets lead to lower prices for risk transfer, maximizing utility

Finally, El Niño/La Niña is well suited to exchange-traded derivatives markets [INSERT COMMENT EXPLAINING BALANCED HEDGING INTEREST ON A TWO SIDED MARKET] because it would facilitate the direct transfer of risk among a diverse collection of hedgers across the world. El Niño/La Niña affects many regions of the globe and within each high-risk region some industries benefit from extreme events (such as reinsurers who historically face fewer losses thanks to suppressed hurricane activity during extreme El Niño) while others suffer. Direct risk trades between those groups would contribute to price discovery and provide sustainable liquidity.

Cite negative relationship with hurricanes Great deal of competition driving prices lower, if they are allowed to entry. Holders of hurricane risk likely to remain speculators because ENSO is not a perfect hedge But good portfolio effects (even if it's not included as a hedge)

3.7 Considerations regarding feasibility of a traded market - The paradox of liquidity

Important research question: Does information about ENSO change sufficiently frequently to warrant trading? Beyond what we can tackle here.

3.7.1 Pricing tools important for catalyzing the emergence of new markets We provide the first stab at those tools here

Baseline index pricing lowers transaction costs for entering the market
 Reduces asymmetric information and price volatility
 Increases confidence in market

Implications of no traditional arbitrage Evidence from other derivatives (HDD, et)

3.7.2 Once we have this data we can ask additional questions whose answers will indicate the likelihood of reaching sustainable liquidity?

Is there meaningful informational change? If information doesn't change, dynamic pricing not needed and insurance markets suffice (despite their limitations)

Are there opportunities to identify mispricing?

4 Methods: Understanding ENSO, information and pricing

4.1 Data considerations, identifying an index

Need to pick:

- Methodology
- Region
- Absolute or anomalies (not so important here)

4.1.1 ERSST vs. OISST

NOAA publishes two primary sea surface temperate indexes. By and large, those indexes tell the same story about El Niño/La Niña.

NOAA's Extended Reconstructed Sea Surface Temperature Index (ERSST) dataset provides a longer record, while NOAA's Optimum Interpolation Sea Surface Temperature Index (OISST) offers finer resolution.

The key factor distinguishing ERSST from OISST is the use of in-situ and satellite data. With the exception of version 3 [footnote ERRST version 3 included infrared satellite data starting in 1985. NOAA determined that this addition introduced some biases into the index - it tended to suggest temperatures that were too cold by a factor of .01 deg C. NOAA consequently removed satellite data (although it retains in situ data collected via satellite) from the calculation of ERSST version 3b, the current standard.], all the ERSST iterations (1,2, and 3b, the iteration used here) use in-situ measurement exclusively[Smith and Reynolds(2004)][Smith and Reynolds(2003)][Smith et al.(2008)Smith, Reynolds, Peterso

Monthly anomalies in the ERSST version 3b index are measured relative to a 1971-2000 base period[Xue et al.(2003)Xue, Smith, and Reynolds]. NOAA releases monthly ERSST estimates with a resolution of two degrees across the four ENSO regions. While the primary index record that NOAA posts to its websites goes back to 1950, monthly ERSST data are available from 1854 on.

OISST, currently at version 2, combines in situ SST measurements, daytime and nighttime satellite data readings, and data from sea ice cover simulations. The satellite data is adjusted statistically for natural sources of bias, like cloud cover and atmospheric water vapor[Reynolds et al.(2002)Reynolds, Rayner, Smith, Stokes, and Wang] [Reynolds and Smith(1994)] [Reynolds and Marsico(1993)] [Reynolds(1988)].

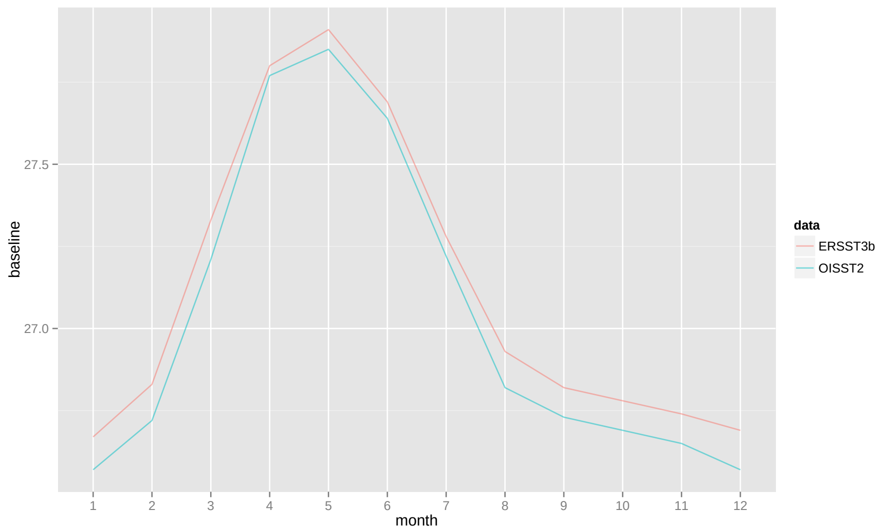

Figure 1: Comparing OISST and ERSST monthly baselines

Figure 1 provides the baseline monthly values that NOAA uses to calibrate anomalies in OISST and ERSST. Note OISSTs tendency toward colder SSTs. The cold bias in satellite data is a great concern in the climate literature and is noted in all the index construction papers on ERSST and OISST cited above.

Note also that February/March and June/July are inflection periods, moving both indexes from cold to warm phases (the former months) and back (the latter months). The baseline SST fluctuations over these two windows is dramatic. I suspect that those months will consequently host very active trading, if traded ENSO markets launch. Those are also likely to be the months where climate expertise and proprietary data will provide the largest edge to traders. The possibility of information asymmetries in those months may undermine the volume boost that traded markets might otherwise get from increased volatility.

Result ERSST

4.1.2 Niño region

Niño 1.2 is the best predictor of catastrophic flooding in Peru and Ecuador, El Niño's flagship impact. However, NMS generally mark ENSO anomalies using the Niño 3.4 region[1] (roughly, from 5°N to 5°S and from 120° to 170°W), which stretches across the central Pacific[Khalil et al.(2007)Khalil, Kwon, Lall, Miranda, and Skees]

[1] Niño 3.4, straddles two separate regions, Niño 3 and Niño 4.

[Barnston et al.(1997)Barnston, Chelliah, and Goldenberg]. Both regions, Niño 1.2 and the Niño 3.4, have a very high correlation during extreme anomalies. But Niño 3.4 is generally considered a better proxy for the worldwide teleconnections associated with ENSO. In particular, it does a better job capturing ENSO anomalies with different geographic signatures. During the 1972/1973 El Niño, for example, most of the sea-surface temperature warming occurred in the central Pacific, closer to Niño 3.4. El Niño events focused on the Central Pacific are also called *Modoki* Niños and can have large global impacts[Ashok et al.(2007)Ashok, Behera, Rao, Weng, and

Result use Niño 3.4

4.1.3 Anomalies vs. absolute SST measurements

NOAA releases each of its datasets as departures from monthly averages (anomalies) and absolute degrees Celsius. Its not immediately clear which format is better for financial contracts.

Presenting contracts in terms of anomalies facilitates interpretation of actual El Niño/La Niña events, since most major meteorological organizations define those events in terms of persistent monthly anomalies. Indeed, many forecasts of SSTs (like those from the ABM and IRI) are only provided in terms of anomalies.

The primary disadvantage of anomalies is that they have been, and will continue to be, subject to revision as underlying SSTs drift over time.

[THERE IS] a possible [BUT WEAK] link between climate change and higher Pacific SSTs.

To the extent that such trends continue, the index may revise its baseline and the interpretation of anomalies may become less clear. The ONI index, which NOAA uses to define El Niño/La Niña already uses a rolling window for its monthly base periods.

The weather traders I interviewed [give context] suggested that the temperature derivatives are currently subject to annual revision. The practice has not been a problem for traders. Nevertheless, there may be advantages to using absolute SSTs. Absolute measurements will directly incorporate any underlying shifts in the index, allowing, for example, traders to simply express theories about the long-term trends in the index. Those theories and, by proxy, the market's judgment of long-term climate change might be obscured in an anomaly-based contract.

4.2 Developing a prototypical contract

According to Dr. Andrew Watkins of the Australian Bureau of Meteorology (ABM), October is the single most decisive month for El Niño/La Niña worldwide. It is consequently the month I use for most of the examples in this chapter.

I am most concerned with extreme El Niño/La Niña, so I've chosen to structure the payout functions for my example options around events between one and three standard deviations away from the monthly mean. More specifically, payments on the options begin at one standard deviation[2] above or below the monthly average (for El Niño coverage/calls and La Niña coverage/puts respectively) and payments reach one hundred percent of the notional value (or sum insured) at three standard deviations above or below the monthly average. Figure 2 shows the average monthly value for Niño 3.4 in black. The red and blue bands show the index values for each month that would trigger a payment on calls and puts respectively.

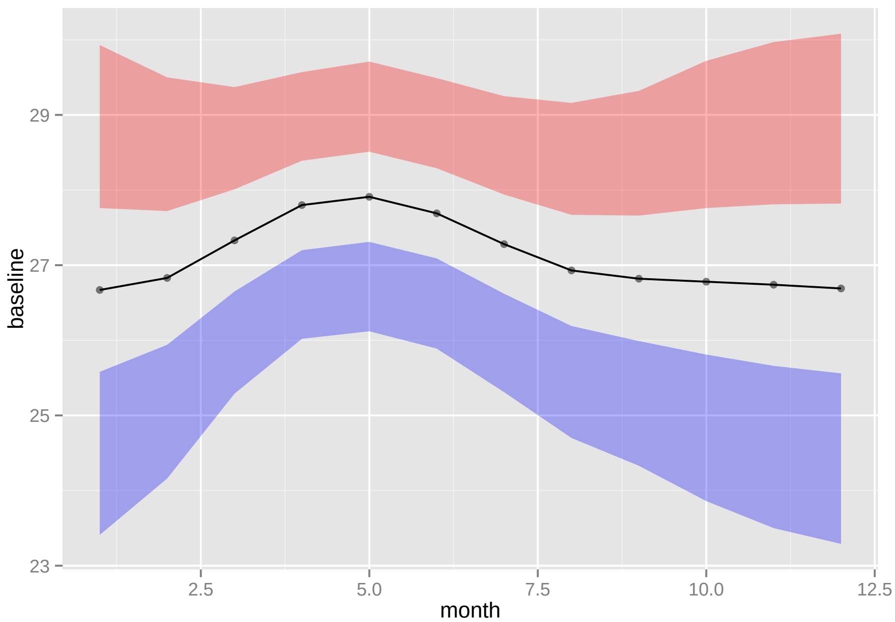

Figure 2: Index values for El Niño (red) and La Niña (blue) events between one and three standard deviations away from monthly average

Within those ranges, I use linear pricing such that an index value halfway across the red band in figure 2 (i.e. halfway between the the trigger and max payout point) would obligate a payout that is half of the sum insured on a call/El Niño contract. The full linear function for October El Niño is shown in figure 3.

As an example, suppose that I bought USD 100 of coverage for USD 10 against October El Niño. If actual October SST was halfway across the red band, or 28.74°C, I would receive USD 50.

In practice, GlobalAgRisk found that hedgers (and speculators) prefer a payout function that offers a minimum payout in the event that the index reaches just above the trigger. For example, an index value that just barely crosses into

[2] This is also called the trigger or attachment point.

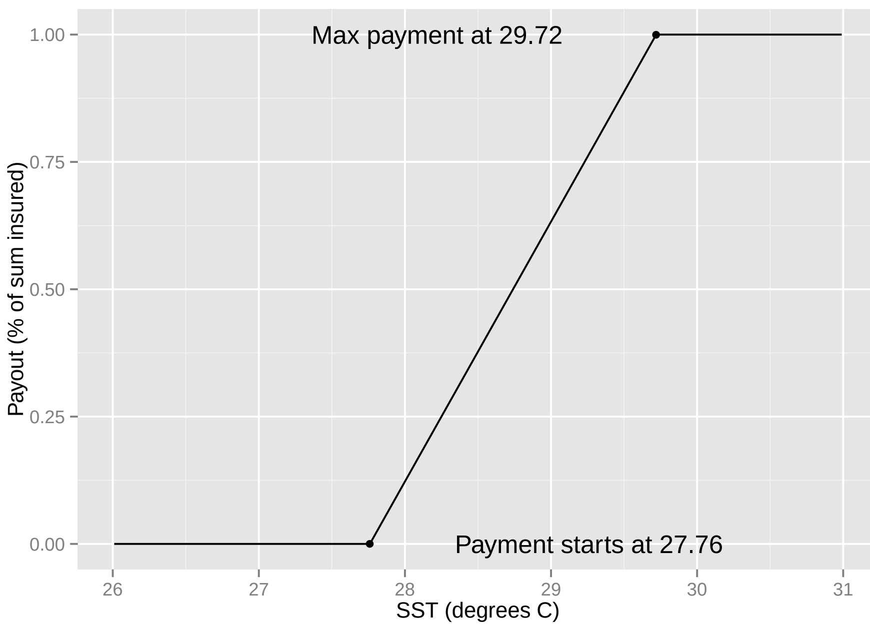

Figure 3: Payout function for call option on October SST for Niño 3.4 ERSST.3b covering index values between one and three standard deviations above the baseline

the red in 2 might trigger a payout of 5 percent on an El Niño/call contract, rather than the tiny payout suggested the kind of linear function in figure 3.

Some potential clients also expressed interest in a more customized payout function consisting of steps usually shaped around historical events e.g. a 25 percent payout for the 1972/1973 magnitude event and a 75 percent for a 1997/1998 magnitude event.

4.2.1 Result

suggest 1-3 s.d. coverage, put and call

4.3 Distribution

In figure 4, I show the prices generated (in USD of premium per USD 100 of nominal coverage) from the random samples from fit distributions. The figure includes burn prices and prices from samples taken from kernel density smoothers fit over each month.

The prices from the various distributions are, with one prominent exception, close together. On the El Niño side, the highest and lowest prices are mostly within 125 basis points of one another in any given month. On the La Niña side, that spread is slightly larger at roughly 150 basis point, but only between April and June.

The Weibull, is the one model challenging this consensus. The prices from the Weibull samples are clearly distinct from the rest of the group - almost doubling the price of La Niña coverage relative to the rest of the group. The Weibull sample suggested the lowest prices for El Niño coverage, albeit by a much smaller margin than for La Niña. That is understandable given the distribution's heavy left tail.

Apart from the Weibull, the samples drawn from the kernel density smoother suggests the second highest prices for both El Niño and La Niña coverage. The burn prices are in the middle of the pack.

4.3.1 Result

robust to several distributional assumptions. Using normal has advantages

4.4 Picking a forecast

Forecasts, IRIs ensemble, and error around the ensemble forecast

4.4.1 Result 1

IRI ensemble good foundation for baseline

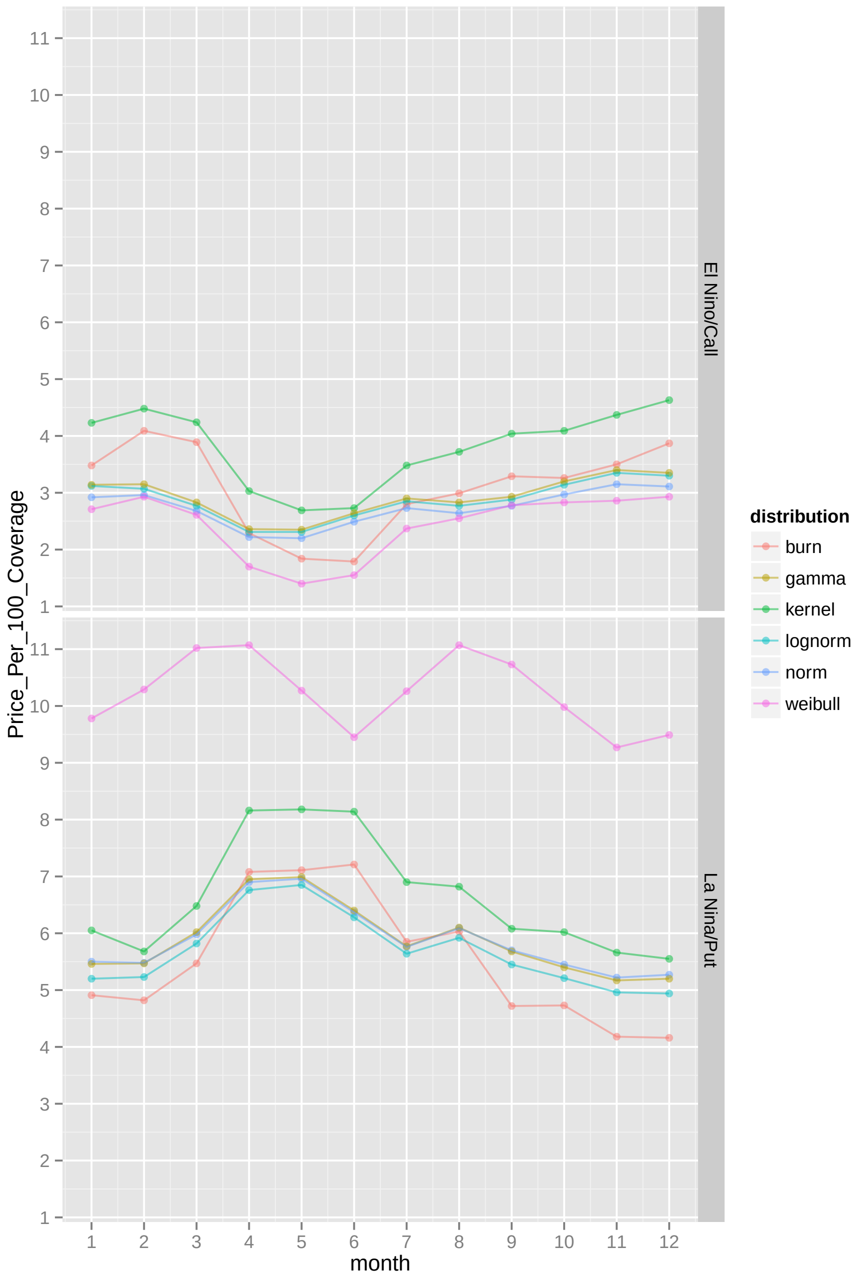

Figure 4: Expected price for options on Niño 3.4 by month, based on simulations from various distributions

4.5 Pricing ensemble error

Extreme El Niño/La Niña events emerge over time, with forecasts giving us even more useful hints in the months leading up to a given event. As those hints emerge, we change our beliefs around the likelihood of an event. The price of El Niño/La Niña risk protection should change to reflect those beliefs.

In this section, I present pricing analysis conditioned on SST forecasts released by Colombia University's International Research Institute for Climate and Society (IRI). Every month since mid-2002, IRI has collected forecasts issued by major centers of climatological research. Figure 5 shows IRI the forecasts as of March 2013.

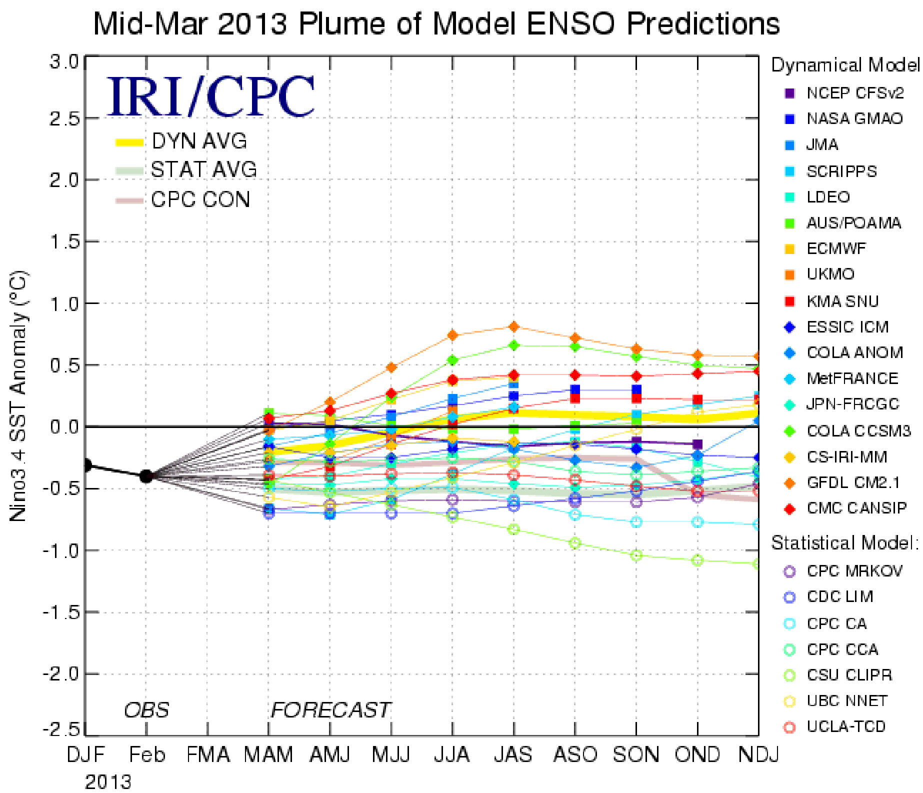

Figure 5: Example of IRI's collected forecasts - March 2013

I link forecasts and observed SSTs through a Bayesian regression that uses the long terms climate record as a prior. If the regression indicates that the forecasts have no predictive power, then all the simulated SSTs from the regression will simply reflect monthly historical averages.

4.5.1 Modeling the link between forecasts and SSTs

As an example, imagine that it is March and I am interested in predicting October Niño 3.4 SST. IRI's forecasts (given in terms of anomalies) are smoothed using three-month blocks, as in figure 5. In that figure, there are three forecasts that contain information relevant to October SSTs - *ASO*, *SON*, and *OND*.

There are myriad ways of combining both individual and average forecasts for those three windows in a regression, but in this section I use as my predictive variable the IRI model average. So, in the above example, I would look at all the model averages made in March for *ASO*, *SON*, and *OND*, taking the average of those three numbers in any given year. I did the same for every month across that months valuable forecasts. That forecast average then conditions the long-term average anomaly for October[3]. IRI issues forecasts between 2 and 10 months prior to any given target month. For example, October SST forecasts begin in December and end in September. Since I want pricing for every month, from the vantage-point of every preceding month with IRI forecasts, I need to run a total of 108 separate regressions.

$$
\begin{aligned}
\text{Monthly Niño 3.4 ERSST.3b anomalies}_{month,year} &\sim \mathcal{N}(\hat{y}_{month,forecastmonth,year}, \sigma^2_{y_{month,forecastmonth}}) \\
\hat{y}_{month,forecastmonth,year} &= a_{month,forecastmonth} \\
&\quad + b_{month,forecastmonth} * \\
&\quad \text{average of IRI average forecasts}_{month,forecastmonth}
\end{aligned} \tag{1}
$$

Those regressions, specified in equation 1, are a simplified version of a procedure that climate scientists and statisticians have recently used to merge ENSO forecasts[Luo et al.(2007)Luo, Wood, and Pan][Coelho et al.(2004)Coelho, Pezzulli, Balmaseda, Doblas-Reyes, Note first that I do not know the predictive power of IRI average forecasts. The parameter $\sigma^2_{y_{month,forecastmonth}}$ accounts for that forecasting uncertainty. It will be large where IRI average forecasts have shown low historical predictive power. Note also that this Bayesian regression will not be biased by non-stationarity. The underlying parameters are not assumed to be stationary, since they are realizations of an unknown distribution.

The prior probabilities I placed on model parameters are shown in equation set 2. There are weakly informative priors on b and σ_y, allowing them to move easily across a wide range of possible values in response to the data. a by contrast has a strongly informative prior based on historical data. This means that if b, the parameter indicating the predictive power of IRI's average forecasts, is at or near zero, then the resulting simulations from the posterior distribution will simply reflect long term trends in monthly SSTs.

$$
\begin{aligned}
a_{month,forecastmonth} &\sim \mathcal{N}(\text{mean anomalies}_{month}, \text{st dev anomalies}_{month}) \\
b_{month,forecastmonth} &\sim \mathcal{N}(0, 100) \\
\sigma^2_{y_{month,forecastmonth}} &\sim \text{Inv gamma}(0.001, 0.001)
\end{aligned} \tag{2}
$$

[3] I used anomalies rather than absolute SSTs to match IRI's convention.

4.5.2 Dynamic pricing based on model results

The table below contains regression results for October SSTs, predicted between the preceding December and August. The regressions were all estimated using parallel Markov Chain Monte Carlo (MCMC) chains, each with 100,000 iterations, 50,000 of which were discarded as a warm-up[Stan Development Team(2013)].

[CHANGE] The $\hat{R}$ on all parameters below and in part Pricing Appendix were 1, indicating convergence on the simulation.

	mean	sd	2.5^{th} q	25^{th} q	50^{th} q	75^{th} q	97.5^{th} q	n_eff	Rhat
August forecast average covering October Niño 3.4 SST anomalies									
α	-0.10	0.10	-0.40	-0.20	-0.10	-0.10	0.10	91045	1
β	1.10	0.20	0.80	1.00	1.10	1.20	1.50	88920	1
σ_y^2	0.10	0.10	0.10	0.10	0.10	0.20	0.40	56829	1
July forecast average covering October Niño 3.4 SST anomalies									
α	-0.10	0.20	-0.50	-0.20	-0.10	0.00	0.20	92218	1
β	1.20	0.30	0.60	1.00	1.20	1.30	1.70	93712	1
σ_y^2	0.30	0.20	0.10	0.20	0.30	0.40	0.90	54297	1
June forecast average covering October Niño 3.4 SST anomalies									
α	-0.10	0.20	-0.40	-0.20	-0.10	0.00	0.30	95908	1
β	1.40	0.30	0.70	1.20	1.40	1.60	2.10	91107	1
σ_y^2	0.30	0.20	0.10	0.20	0.30	0.40	0.90	55596	1
May forecast average covering October Niño 3.4 SST anomalies									
α	-0.10	0.20	-0.50	-0.20	-0.10	0.10	0.40	92919	1
β	1.50	0.60	0.40	1.20	1.50	1.90	2.60	90255	1
σ_y^2	0.50	0.30	0.20	0.30	0.50	0.60	1.40	59205	1
April forecast average covering October Niño 3.4 SST anomalies									
α	-0.10	0.20	-0.50	-0.30	-0.10	0.00	0.30	88326	1
β	1.90	0.60	0.70	1.50	1.90	2.30	3.00	83902	1
σ_y^2	0.40	0.30	0.20	0.30	0.40	0.50	1.10	57674	1
March forecast average covering October Niño 3.4 SST anomalies									
α	0.00	0.20	-0.50	-0.10	0.00	0.20	0.50	101040	1
β	1.80	0.90	0.00	1.20	1.80	2.30	3.50	96782	1
σ_y^2	0.70	0.50	0.30	0.50	0.60	0.90	1.90	59539	1
February forecast average covering October Niño 3.4 SST anomalies									
α	-0.10	0.30	-0.70	-0.30	-0.10	0.10	0.60	98192	1
β	0.80	1.30	-1.80	0.00	0.80	1.60	3.40	88684	1
σ_y^2	1.10	0.80	0.40	0.60	0.90	1.30	3.20	54912	1
January forecast average covering October Niño 3.4 SST anomalies									
α	0.00	0.30	-0.60	-0.20	0.00	0.20	0.60	99518	1
β	1.00	1.60	-2.30	0.00	1.00	2.00	4.20	92225	1
σ_y^2	1.00	0.70	0.40	0.60	0.80	1.20	2.80	55715	1
December forecast average covering October Niño 3.4 SST anomalies									
α	0.00	0.30	-0.60	-0.20	0.00	0.30	0.70	80946	1
β	-0.30	1.90	-4.00	-1.40	-0.30	0.90	3.50	76663	1
σ_y^2	1.10	0.70	0.40	0.60	0.90	1.30	2.90	56323	1

Table 1: [

10pt]Bayesian regression linking October Niño 3.4 SST anomalies to average of relevant IRI ensemble forecasts

Looking at the 2.5th and 97.5th percentile of the distributions for b, its clear that the forecasts become more valuable predictors as the year goes on. Going from December to August, the 95 percent probability interval for the forecast parameter, b steadily tightens to a range including 1. This suggest that the correlation between forecasts and eventual SSTs increases throughout the predictive window. As the explanatory value of b increases, a decreases. Just as climate scientists suggested, a's 95 percent probability tightening around 0 after March.

Using the posterior draws of parameter values from these 108 regressions, I simulated SSTs predicted by each possible forecast value between -2 and 2 (forecasts are rounded to one decimal). For example, I took 50,000 posterior draws of a, b, and σ_y^2 from the regression corresponding to October SSTs predicted by April forecasts. I used each of those 50,000 vectors of three parameters to randomly generate one October SSTs, based on an average April forecast of mild El Niño conditions in the coming October (a forecast value of 0.5.) That left me with 50,000 October SST conditioned on a forecast of 0.5 made in April. I repeated that procedure to produce conditional distributions for SSTs for each month of the year, predicted by a wide range of forecast values, from all possible forecast months. The resulting stochastic catalog allowed me to price El Niño/La Niña risk for any month given any IRI average forecast.

The empirical distribution functions of those posterior simulations, converted back into absolute SSTs, are shown in figures 6 and 6. In those figures, deeper blue lines indicate colder forecast averages from IRI and deeper red lines indicate warmer forecasts.

Notice how the blue and red lines are tightly bound ten months prior to any given target month (down the rightmost column) in figures 6 and 7. This indicates that forecasts had little or no predictive power, as warm forecasts were as closely associated with eventual warm conditions as cold forecasts, and visa versa. In some cases, where the blue lines peek above the red, the colder forecasts are actually associated with higher eventual SSTs. The fact that the red and blue lines bunch together as you move left to right across rows in figures 6 and 7 suggests that the signal from IRI's average forecasts deteriorates as we go further back in the predictive window.

By contrast, two months away from a target month (down the leftmost column of figures 6 and 7), forecasts are meaningful. Blue lines sit below red lines. So a warm forecast shifts the distribution of eventual SSTs warmer and visa versa.

The spring predictive barrier is also clear in the figures. The difference between April outcomes, conditioned on particularly cold and warm forecasts made just two months prior, is smaller than the same difference for February SSTs made ten months out. In visual terms, the ECDFs for row April, column t-2 months are more compact than the ECDFs for row February, column t-10 months. In other words, April SSTs show a weaker link to February predictions than February SSTs show to predictions from the preceding April.

In table 2, I translated these simulation results into pricing for October La Niña protection (put options on October SST). As before in this chapter, I used a payout function that began one standard deviation below normal and

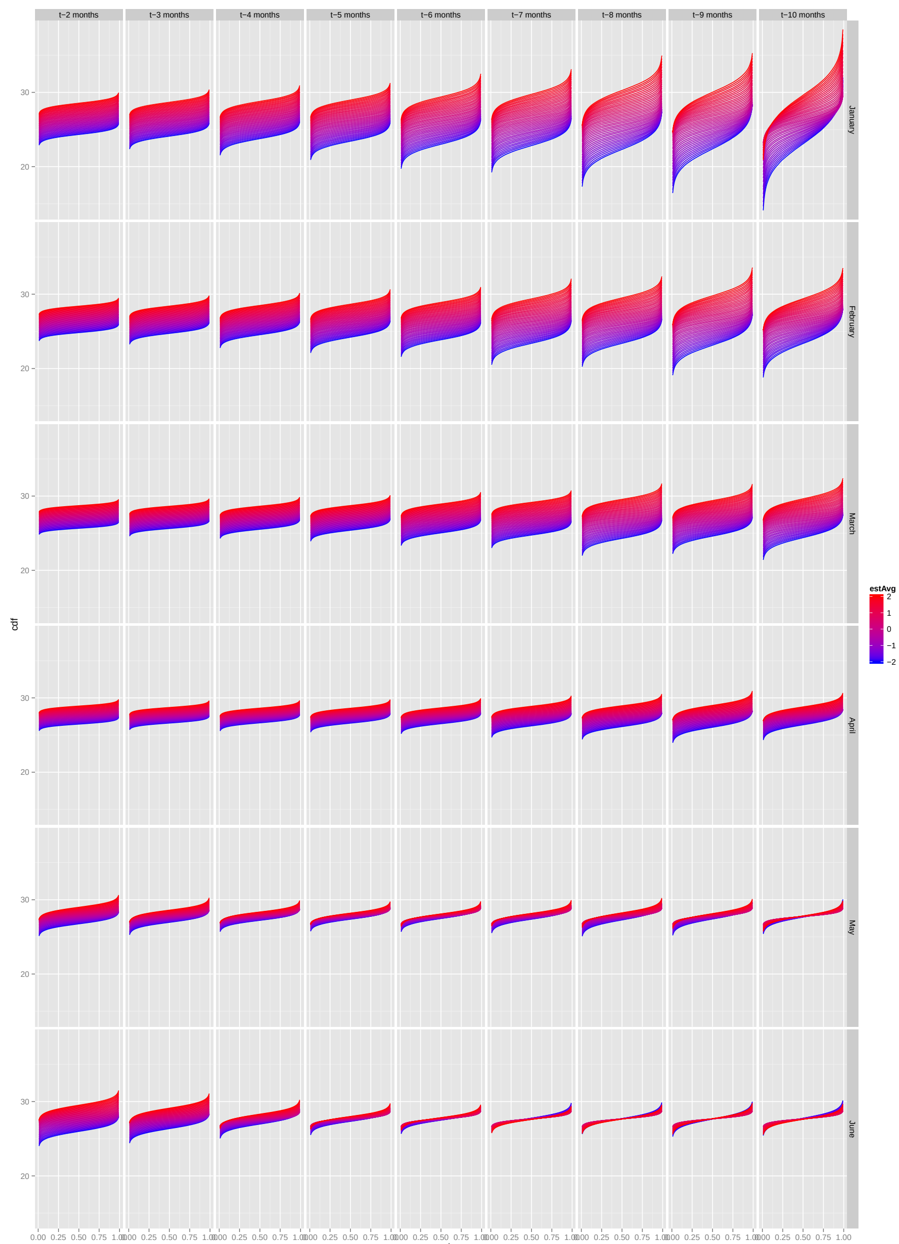

Figure 6: Cumulative distribution functions for realized January through June Niño 3.4 SST conditioned on average IRI ensemble forecasts for various months

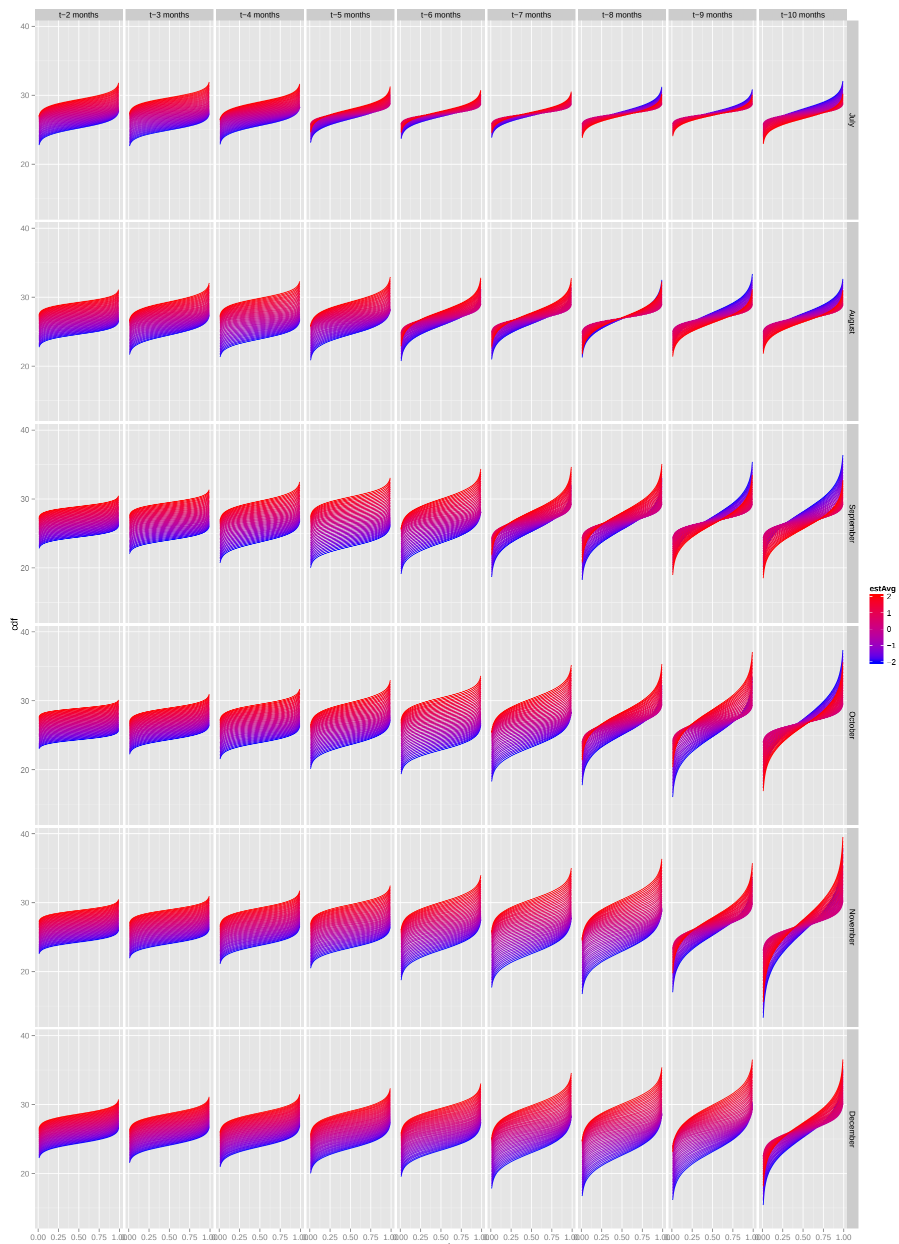

Figure 7: Cumulative distribution functions for realized July through December Niño 3.4 SST conditioned on average IRI ensemble forecasts for various months

reached 100 percent of the nominal value of the agreement (sum insured) at three standard deviations below normal. The full conditional pricing tables for all months, covering both El Niño and La Niña, are available [ONLINE].

4.5.3 Result 1

stochastic catalog

4.5.4 Result 2

Information is more important at some points than others

5 Application

5.1 Key changes to make this operational

The prices in table 2 and [ONLINE] only reflect the underlying risk of the index. In actual transactions, these pure risk prices will generally be:

- adjusted (downward) to reflect the time value of the premium paid by hedgers;
- subjected to some margining[4] rules, when applicable; and
- adjusted (upward) to allow for some reasonable expected profit for speculators.

5.2 Understanding informational and monetary gains from better forecasts

5.3 Remove best forecast and compare pricing with and without it. What is the earning opportunity?

5.4 Alternatively: application of finding natural swaps

6 Conclusion

6.1 Key results summary

6.1.1 Distributional properties several assumptions seem to work

Normality assumption works well (and may have analytical benefits?)

[4] Margining refers to the process of setting aside collateral on financial trades. On exchange-traded derivatives there are clear, predictable rules for how much money must be set aside as collateral in a *margin account* as the trade's settlement index changes over time.

6.1.2 Information changes significantly and so motivates dynamic pricing

Inflection points and critical information

Identifying the magnitude of uncertainty and its pricing implications

IRI ensemble forecast can provide foundation for baseline

6.2 Other necessary conditions for traded market

6.3 Positive externalities

6.3.1 Better climate models (O.J. futures example)

6.3.2 Should government finance the startup?

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IRI anom	price per USD	E[SST]	2.5^{th} q	25^{th} q	50^{th} q	75^{th} q	97.5^{th} q
-2.00	0.80	23.93	0.00	0.66	0.96	1.00	1.00
-1.90	0.77	24.07	0.00	0.59	0.89	1.00	1.00
-1.80	0.73	24.21	0.00	0.54	0.82	1.00	1.00
-1.70	0.68	24.35	0.00	0.47	0.75	1.00	1.00
-1.60	0.64	24.49	0.00	0.41	0.68	0.95	1.00
-1.50	0.58	24.63	0.00	0.34	0.60	0.87	1.00
-1.40	0.53	24.77	0.00	0.28	0.54	0.79	1.00
-1.30	0.47	24.91	0.00	0.21	0.47	0.71	1.00
-1.20	0.41	25.05	0.00	0.15	0.39	0.63	1.00
-1.10	0.35	25.19	0.00	0.08	0.32	0.55	1.00
-1.00	0.30	25.33	0.00	0.02	0.25	0.48	0.99
-0.90	0.24	25.47	0.00	0.00	0.18	0.40	0.90
-0.80	0.19	25.60	0.00	0.00	0.11	0.33	0.81
-0.70	0.15	25.74	0.00	0.00	0.03	0.25	0.72
-0.60	0.11	25.88	0.00	0.00	0.00	0.17	0.63
-0.50	0.08	26.02	0.00	0.00	0.00	0.10	0.55
-0.40	0.06	26.16	0.00	0.00	0.00	0.02	0.46
-0.30	0.04	26.30	0.00	0.00	0.00	0.00	0.38
-0.20	0.02	26.44	0.00	0.00	0.00	0.00	0.31
-0.10	0.02	26.58	0.00	0.00	0.00	0.00	0.23
0.00	0.01	26.72	0.00	0.00	0.00	0.00	0.16
0.10	0.01	26.86	0.00	0.00	0.00	0.00	0.08
0.20	0.00	26.99	0.00	0.00	0.00	0.00	0.01
0.30	0.00	27.14	0.00	0.00	0.00	0.00	0.00
0.40	0.00	27.27	0.00	0.00	0.00	0.00	0.00
0.50	0.00	27.41	0.00	0.00	0.00	0.00	0.00
0.60	0.00	27.55	0.00	0.00	0.00	0.00	0.00
0.70	0.00	27.69	0.00	0.00	0.00	0.00	0.00
0.80	0.00	27.83	0.00	0.00	0.00	0.00	0.00
0.90	0.00	27.97	0.00	0.00	0.00	0.00	0.00
1.00	0.00	28.11	0.00	0.00	0.00	0.00	0.00
1.10	0.00	28.24	0.00	0.00	0.00	0.00	0.00
1.20	0.00	28.38	0.00	0.00	0.00	0.00	0.00
1.30	0.00	28.53	0.00	0.00	0.00	0.00	0.00
1.40	0.00	28.67	0.00	0.00	0.00	0.00	0.00
1.50	0.00	28.80	0.00	0.00	0.00	0.00	0.00
1.60	0.00	28.95	0.00	0.00	0.00	0.00	0.00
1.70	0.00	29.08	0.00	0.00	0.00	0.00	0.00
1.80	0.00	29.23	0.00	0.00	0.00	0.00	0.00
1.90	0.00	29.36	0.00	0.00	0.00	0.00	0.00
2.00	0.00	29.51	0.00	0.00	0.00	0.00	0.00

Table 2: [
10pt]Put option prices for October Niño 3.4 SST conditioned on IRI ensemble forecasts released in June