Supporting the Development of Direct Climate Markets: Pricing Uncertainty in ENSO Forecasts

1 Introduction

Existing financial and insurance markets fail to provide protection against, and clear forecasts of, climate risk. There are many markets today where firms and individuals can trade or manage risk influenced by climate. Among the better known are traded markets for emission permits, temperature and rainfall derivatives for major cities, and equities for companies in weather dependent industries. Similarly, there are markets for insurance and reinsurance risks which are only traded by specialized institutional investors (Kurtov; 2010)[INSERT CHAPTER SPECIFIC REF]. But none of these markets offer at-risk communities direct protection from climate extremes at competitive prices prices that represent an informed forecast of global weather patterns. Instead, prices on these markets are primarily driven by non-climate factors like policy and recent returns in bond and equity markets (The Economist; 2013) (Kurtov; 2010)[INSERT CHAPTER SPECIFIC REF]. This discrepancy between a risk as it is experienced by individuals and the index underlying a market where individuals could manage that risk is an example of what is called in finance *high basis risk*.

One alternative to existing markets could be markets based on basic indexes of climate change, like the extent of Arctic ice or global mean surface temperatures. But, meaningful shifts in these indexes, if they occur as seem likely according to current climate models, will play out over long-time horizons I (2013). Those horizons complicate collective decision making in particular, but they are also a source for disagreement about the merits of hedging climate risk even among experts Jacquet et al. (2013) Nordhaus (2013)[Need SPECIFIC CHAPTER REF OR PAPER REF] Pindyck (2013). Moreover, the models used to simulate global climate change have not progressed to the point where they can translate those global indexes into forecasts of adverse climate events on a geographic scale that is actionable for many firms [Need SPECIFIC CITATION PERHAPS IPCC ON LIMITATIONS OF GLOBAL MODELS]. In this case, an actionable geographic scale would be one focused enough to convince risk managers that a climate risk would imperil specific contractual relationships, a key factor motivating hedging Pennings and Leuthold (2000) Pennings and Leuthold (2001). Hence, it is not clear that there is latent demand for hedges against the indexes that have come to define global climate change.

Together, the difficulties of building meaningful financial contracts directly around climate change and the basis risk inherent to managing climate risk with existing markets suggest a missing market, one that could:

- Directly cover climate risks more pervasive than simple short-term weather indicators;

- Meet conditions associated with stable financial risk transfer flows Working (1953) Silber (1981) Carlton (1984) Black and of Business Administration. Salomon Brothers Center for the Study of Financial Institutions (1986) Duffie and Jackson (1989) Tashjian (1995) Pennings and Leuthold (1999) Brorsen et al. (2001) Gorham and Kundu (2012) Sandor (2012); and

- Fit within the actionable geographic scope and time horizons of decision makers attempting to prepare for a changing climate.

This paper considers whether financial markets for indexes of regional climate anomalies with long-range physical and statistical links to extreme weather events, or what climate scientists call *teleconnections*, might address that market gap.

In particular, El Niño-Southern Oscillation (ENSO) (more specificaly the Oscillation's extreme anomaly events called El Niño/La Niña) is a climate driver with teleconnections whose risk is already directly managed through an innovative insurance that the authors helped design, and facilitate sales of, with support from the Gate Foundation. This emerging El Niño insurance market is noteworthy in that it is the first market to directly hedge teleconnection risk and has been structured as forecast insurance - an insurance that pays based on a remotely measured geophysical event that precedes much of El Niño's physical damage.

The nascent market for El Niño insurance suggests a greater potential to transfer teleconnection risks around the world. Traded risk management tools based on existing El Niño insurance, but relevant to ENSO hedgers across the globe, may the best opportunity to provide at-risk communities with an actionable risk management tool that could be the basis of climate irsk adaptation strategies [SHOULD THIS BE MITIGATION?] and that generates prices whose climate forecast information is of wide social value. ENSO and other indexes with teleconnections directly causing extreme weather in specific communities. Hence these climate drivers are specific enough to worry individuals, firms, and institutions in the short-term. Yet, they are also long-dated and wide-ranging phenomenon, clearly linked to global climate change.

In this article we introduce practical considerations for the development of such markets. We discuss the nature of ENSO risk and why that risk may generate high social welfare gains if it were managed on traded markets. Then, we introduce a pricing framework that is necessary but not sufficient to catalyze early trades those markets. This framework will give benchmark prices to risk managers seeking climate protection, even as new forecast information becomes available. Dealing with such forecast information and placing a price on the uncertainty within that information is a critical hurdle for the development of robust direct climate markets. Indeed the information asymmetries associated with ENSO forecasts have complicated the sale of existing insurance against extreme El Niño in Peru, which we helped design and sell with support from the Gates Foundation.

In addition, to providing a starting point for risk transfer negotiations our pricing framework helps to answer questions of importance to the financial firms that might allocate resources to trading on direct climate markets, such as whether information about extreme ENSO events changes sufficiently to warrant active trading.

1.1 Introduction to ENSO risk

ENSO refers to a coupled oceanic/atmospheric cycle. In normal years, the cycle follows currents and winds (each reinforcing the other) as they bring water along the surface of the Pacific Ocean from South America (the eastern side of the Pacific) to Indonesian and the South Pacific (the western side of the Pacific). As that water travels along the ocean surface, it warms. The resulting mass of warm water sinks as it arrives in the western Pacific and begins circulating back toward Peru along the cold ocean floor. The cycle ends with cold water rising to the surface in the eastern Pacific, sustaining rich fishing grounds off the coast of Peru and Chile.

During an El Niño anomaly, this cycle weakens. Usually starting in March or April, a plume of warmer-than-normal water creeps eastward across the Pacific, lessening the normal temperature gradient from the Western to the Eastern Pacific. When that plume of warmer-than-normal water reaches Peru, it parks a moisture laden air mass off the South American coast. When that mass meets cold air coming east to west

over the Andes mountains, Peru suffers catastrophic downpours and flooding. Those rains generally arrive in the early months of the year following the initial warming.

By contrast, during a La Niña anomaly the normal cycle enhances. More water gets pushed from the South American coast, raising sea-surface temperatures in Australia and Indonesia above normal. That leaves Southeast Asia and Oceania with increased incidence of extreme rains and flooding.

1.1.1 ENSO Risk Characteristics and the Limitations of ENSO Insurance

The physical risk of El Niño/La Niña includes characteristics that are important from the standpoint of risk management. These characteristics allowed GlobalAgRisk to create an innovative El Niño insurance. However, they also suggest why, eventually, ENSO risk may be better managed through traded markets. These characteristics include:

- ENSO anomalies are measured by a relatively simple index. National Meteorological Services (NMS) monitor El Niño/La Niña primarily by measuring sea-surface temperatures (SST) over defined regions of the Pacific Ocean. That means that the the phenomenon can be accurately expressed using freely available data, provided in simple-to-understand units, according to a methodology that is well defined. These qualities are attractive to prospective speculators (those offering El Niño protection in exchange for an expected profit), because they mitigate many of the moral hazard and adverse selection problems inherent to traditional insurance. [INCLUDE JERRY CITATION]

- Anomalies in SSTs translate to discrete risk outcomes that are well understood by at-risk communities. Speculators' preference for simple and reliable indexes are not enough to drive a new insurance market. The indexes must correspond tightly to hedgers/insurance buyers' risk perceptions.[WORKING? DUFFIE? CUNY? TASHJIAN?] That is indeed the case for NOAA's SST indexes.

  Percieved basis risk is particularly low for Peruvian hedgers managing the risk of catastrophic flooding in the country's Northern region using SST measurements from the Niño 1.2 region, directly off the Peruvian coast. In fact, the high SSTs measured by NOAA's various indexes are the immediate physical cause of flooding, so the link between the index and risk outcomes is more a simple statistical associationKhalil et al. (2007).

  Rainfall in northern Peru during the last severe El Niño in 1998 was 40 times normal for January to May (Skees and Murphy; 2009). This event caused widescale internal displacement of people; loss of life; increases water-born illnesses; disruptions to markets and supply chains; and destruction of personal property and critical infrastructure. There were similarly headline-grabbing impacts from the 1983 El Niño.

  Both of those years standout from the rest in Niño SST time series covering the critical months between October and January. This is clear in figure [INSERT FIGURE] which shows the November/December average SSTs for NOAA's Niño 1.2 region, which GlobalAgRisk used as the base index of it's insurance.

  The spikes in that index correspond so well to the years popularly associated with catastrophic El Niño, that most hedgers expressed satisfaction that they would receive some payment should another catastrophic El Niño occur.

- ENSO risk is spatially correlated. Car accidents provide a simple example of what is called a *pooled risk* - everyday that a driver does not get into an accident, they are implicitly paying car insurance premiums that go into a pool used to pay the claims of the few drivers that did get into an accident that day.

By contrast, spatially correlated risks like El Niño cannot be *pooled*. The vast majority of Peruvians facing El Niño risk experience that risk at the same time - every year will either bring a catastrophic El Niño, against which they would like protection, or it will not.

Risks like El Niño that cannot be pooled are generally managed through reinsurance - insurance backed by particularly large companies who have enough capital to payout huge claims at a moments notice. Alternatively, such risks can be managed equally well though traded markets like those for derivatives or securities.

[Need addition about the fact that the GlobalAgRisk was a pass through] [Considering additional additions here but I'm not sure that they are important]

- ENSO has an annual cycle. As mentioned high SSTs in critical months of the year define El Niño/La Niña, but those high SSTs proceed the rains they cause by months. The insurance that GlobalAgRisk designed takes advantage of this lag. It makes payments using November and December ocean temperatures, which predate the severe rains and flooding that begin in January, making it (perhaps) the first regulated forecast insurances in the world. [CHECK IF THE OTHER FORECAST INSUANCE WAS ACTUALLY REGULATED AS INSURANCE OR WAS REINS?] Thus, the insurance payments could be used for loss mitigation and adaptation.

That innovative feature of the insurance is attractive to buyers. However, it rests on the forecast-able nature of ENSO risk, which is problematic for speculators.

The Pacific Ocean does not simply heat up over the course of a month or two. Sustained temperature anomalies build up over months, with the cycle of build-up generally reset at the end of the Northern Hemisphere winter. Each year starting in March, current temperature readings that are warmer or colder than normal SSTs provide probabilistic information about the temperatures that we will see in the critical months later in the ENSO season. The signal provided by those current SSTs strengthens throughout the year, such that forecasts are less reliable in April than they are in June.

That creates a problem for speculators in ENSO risk. If buyers are particularly skilled at forecasting SSTs, they may buy ENSO protection only in those years when they are likely to enjoy a payout. That type of herding behavior is known in insurance markets as adverse selection and (re)insurance companies try to avoid it by setting their *sales closing date*, the last date on which buyers can commit to an insurance arrangement, well in advance of the point at which actionable forecasts emerge.

When GlobalAgRisk's insurance first came on the market in Peru, the sales closing date was set in March. While this was prior to the *spring predictive barrier* in the ENSO cycle, GlobalAgRisk and the reinsurer backing the product were not satisfied that the sales closing date really preceded all actionable forecasts, since new and better forecasts appeared to be under development. In subsequent seasons, the sales closing date for GlobalAgRisk's insurance was pushed back to January, almost a full year before the period of coverage.

This schedule avoids the adverse selection problems created by El Niño forecasts, but it also limits participation in this market. For some firms, the high opportunity cost of purchasing insurance so far in advance is too great. [The next example may not be necessary.] For others, management dynamics constrain their ability to know estimate their El Niño exposure so far in advance. For example, an agribusiness wants to choose its crop allocations in the weeks before the planting season based in part on commodity prices.

Multi-year insurance agreements might alleviate the threat of adverse selection linked to ENSO forecasts, at least for the latter years of those contracts since even ambitious forecasts forecasts rarly

claim to extend uch beyond a year [cite recent ambitious]. But reinsurance and related markets rarely offer standardized risk transfer agreements that extend beyond a year. (Catastrophe bonds, among the longer dated agreement types appropriate to climate change routinely extend out three years, but rarely more than five.) [Need another bridging sentence.]

More importantly, multi-year contracts greatly exacerbate the opportunity cost problem facing insurance buyers. Not only will they require buyers to make a decision on the insurance and lock up primiums ahead of forecasts for the front year of the contract, but they will also have to lock up primiums for the latter years of the contract.

Arguably a better strategy for addressing the forecastability of ENSO risk, is to move the risk onto a traded market where prices for protection will move to reflect new forecast information as it becomes avaliable. With such dynamic pricing of ENSO risk, buyers could enter and exist hedges at their convinience without having to

To be sure, adverse selection can undermine liquidity in traded markets, just as in insurance marketsCopeland and Galai (1983)Glosten and Milgrom (1985)Kyle (1985)Leland (1992). However, many markets routinely incorporate the type of forecast information contained in ENSO forecasts into their prices without those disruptions.

While it is theoretically possible for insurance companies to offer such dynamic pricing, that is not standard practice because it concentrates all of the adverse selection risk at the individual firms selling protection rather than in the mass of traders that may

- ENSO is associated with potentially offsetting consequences across regions and time.

  this means that if you could offer traded markets you could get direct trades. reinsurance doesn't do this.

  No where in the world is more affected by ENSO anomalies than northern Peru and southern Ecuador.

  When oceanic and atmospheric circulation patterns in equatorial Pacific change during El Niño and La Niña, weather systems across the globe shift with major impacts across the Americas, Australia, south and southeast Asia, and Africa [CITE].

  Ropelewski and Halpert (1987) and Ropelewski and Halpert (1989) are seminal papers looking at the footprints of ENSO anomalies between 1875 and 1983. They identify regions (19 for El Niño and 15 for La Niña) where precipitation has a statistically significant link to the ENSO cycle.

- ENSO risk cannot be easily arbitraged using existing markets.

1.2   Traded markets for ENSO

One potential solution to these challenges is structuring ENSO as a traded derivative.

- Better for asymmetric information

    Does not require early closing date

    Can better integrate multi-year trends

    Can integrate information on climate change

- Provision of public information

- Maximizing welfare through lower cost of risk transfer

    Direct risk transfer

    Lower barriers to entry for motivated speculators

1.2.1 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.

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

A primary benefit of dynamic pricing would be better information to guide 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 El Niño/La Niña forecasts 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.

1.2.3 (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 EX-PLAINING 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 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)

1.3 Balanced hedging

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.

2 Methods: Understanding ENSO, information and pricing

[NEED TO DRASTICALLY CUT THESE REGION ETC. sections]

2.1 Data considerations, identifying an index

Need to pick:

- Methodology

- Region

- Absolute or anomalies (not so important here)

2.1.1 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 exclusivelySmith and Reynolds (2004)Smith and Reynolds (2003)Smith et al. (2008).

Monthly anomalies in the ERSST version 3b index are measured relative to a 1971-2000 base periodXue et al. (2003). 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 vaporReynolds et al. (2002) Reynolds and Smith (1994) Reynolds and Marsico (1993) Reynolds (1988).
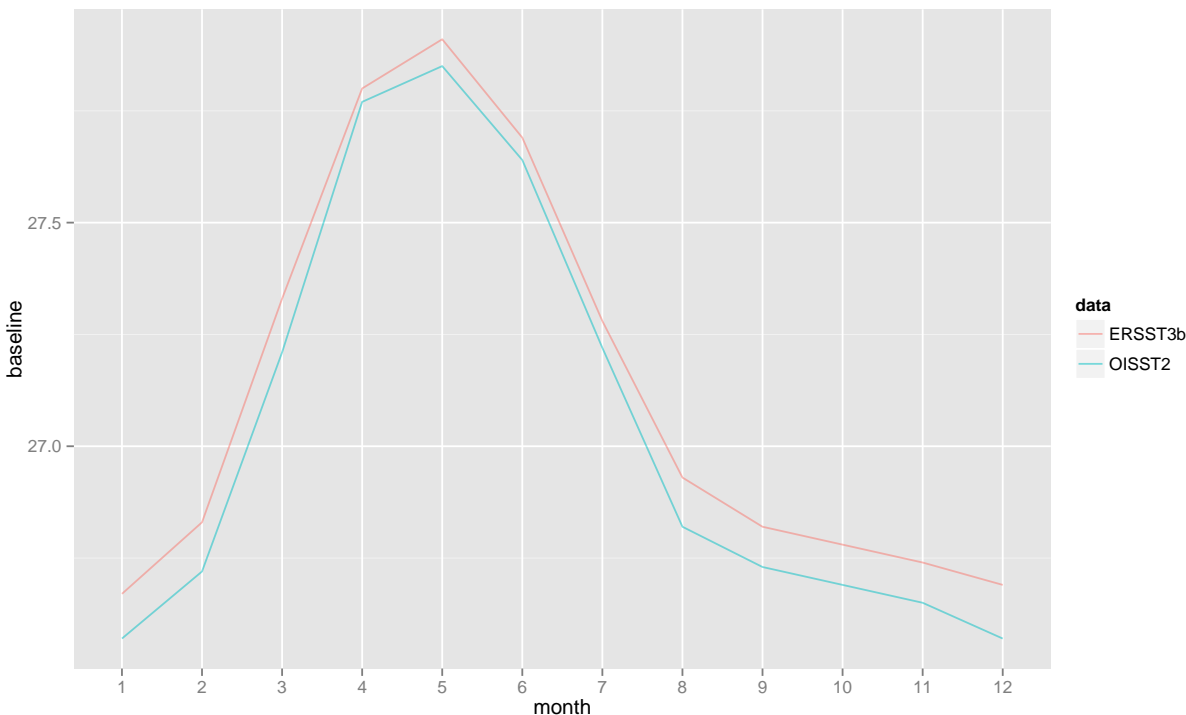

Figure 1: Comparing OISST and ERSST monthly baselines

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

2.1.2 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? Barnston et al. (1997). Both regions, Niño

---

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

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 impactsAshok et al. (2007).

Result use Niño 3.4

2.1.3 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.

2.2 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.

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.

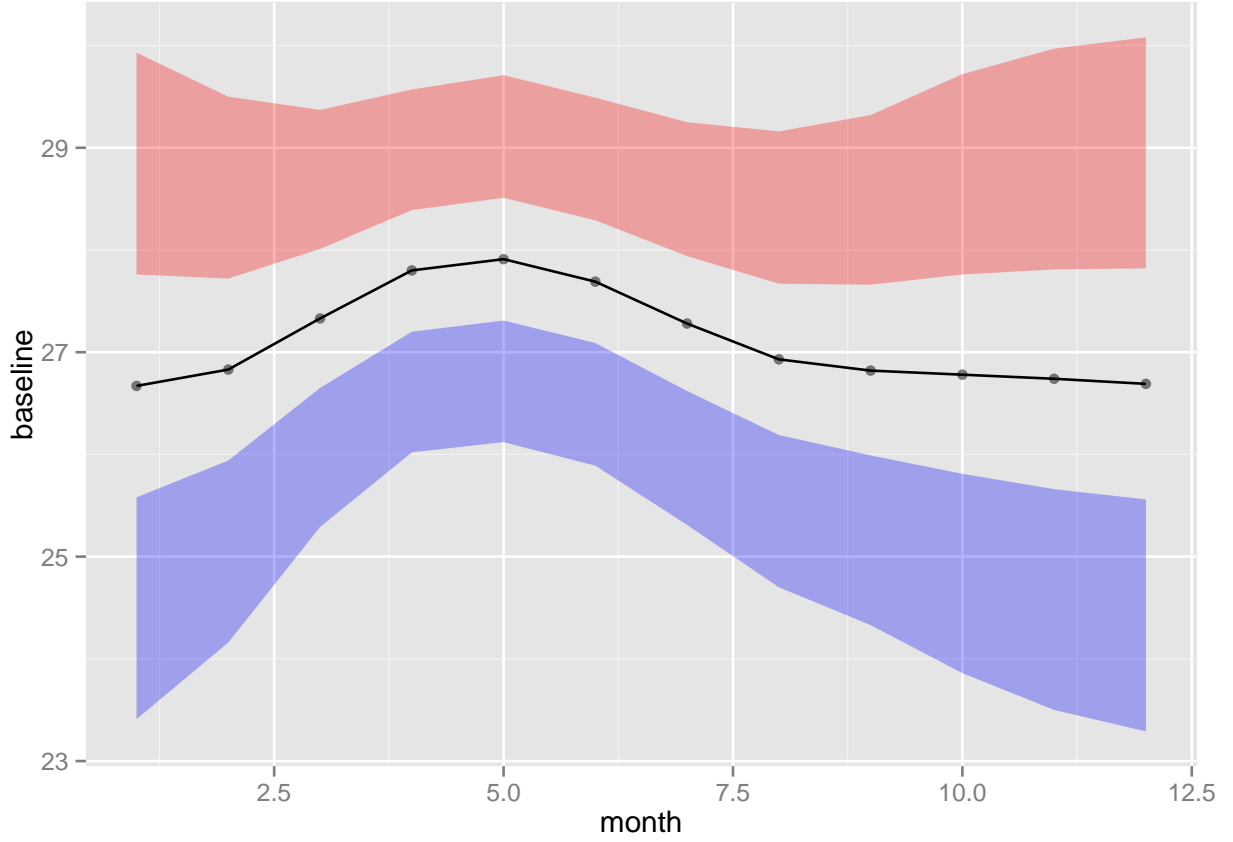[2]This is also called the trigger or attachment point.

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

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 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.

2.2.1 Result

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

2.3 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.
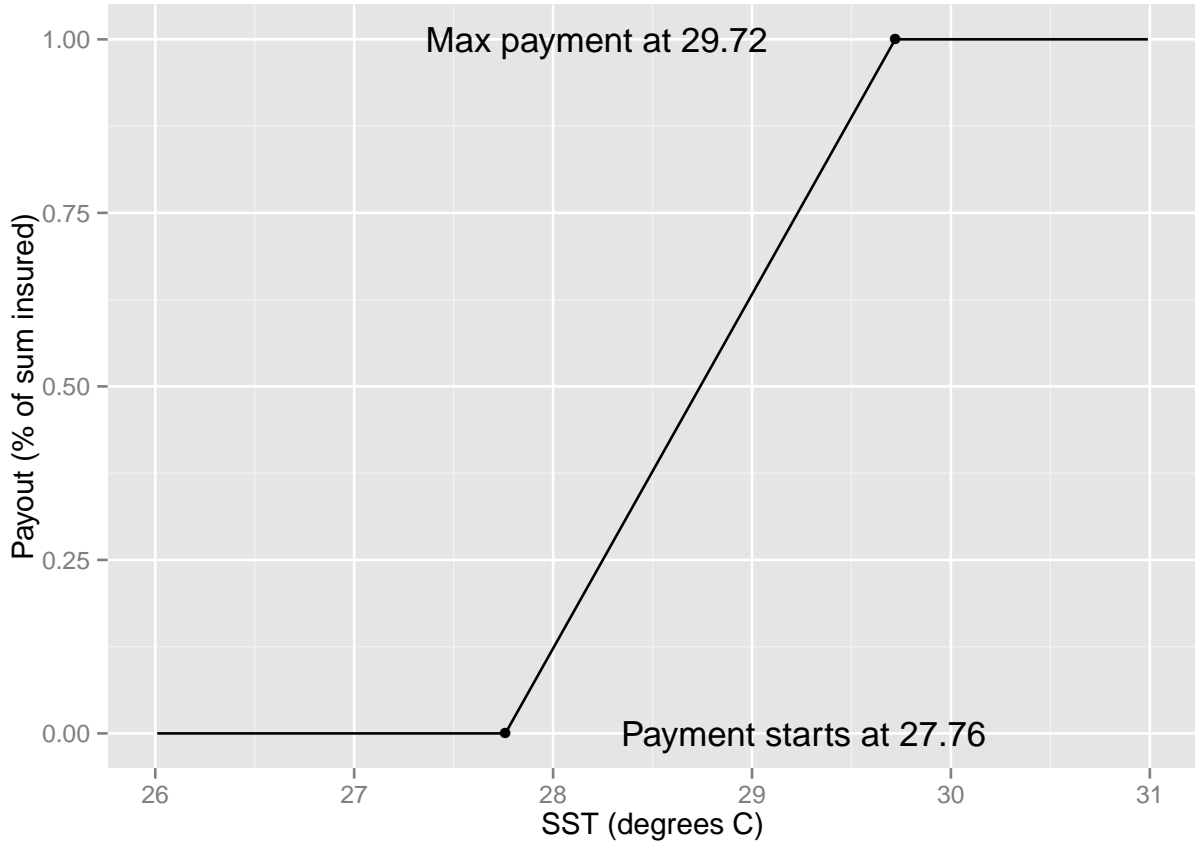
Figure 3: Payout function for call option on October SST for Niño 3.4 ERSST.3b covering index values between one and three standard deviations above the baseline

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.

2.3.1 Result

robust to several distributional assumptions. Using normal has advantages

2.4 Picking a forecast

Forecasts, IRIs ensemble, and error around the ensemble forecast

2.4.1 Result 1
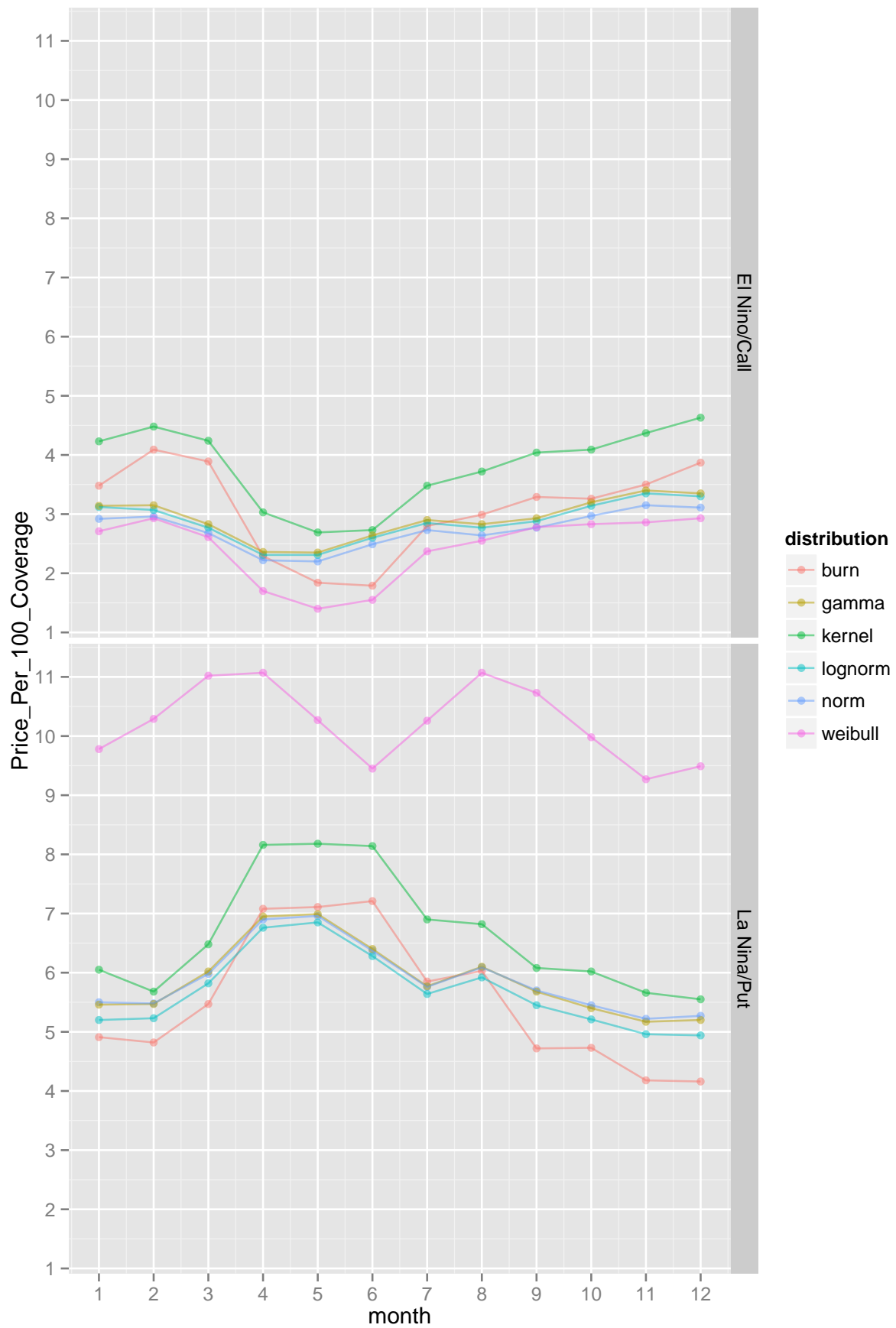
IRI ensemble good foundation for baseline

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

2.5 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, we present statistical simulations of monthly Niño 3.4 sea surface temperatures conditioned on average forecasts released by Colombia University's International Research Institute for Climate and Society (IRI). We use those simulations to update the prices of risk management contracts as new forecast information becomes available.

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.
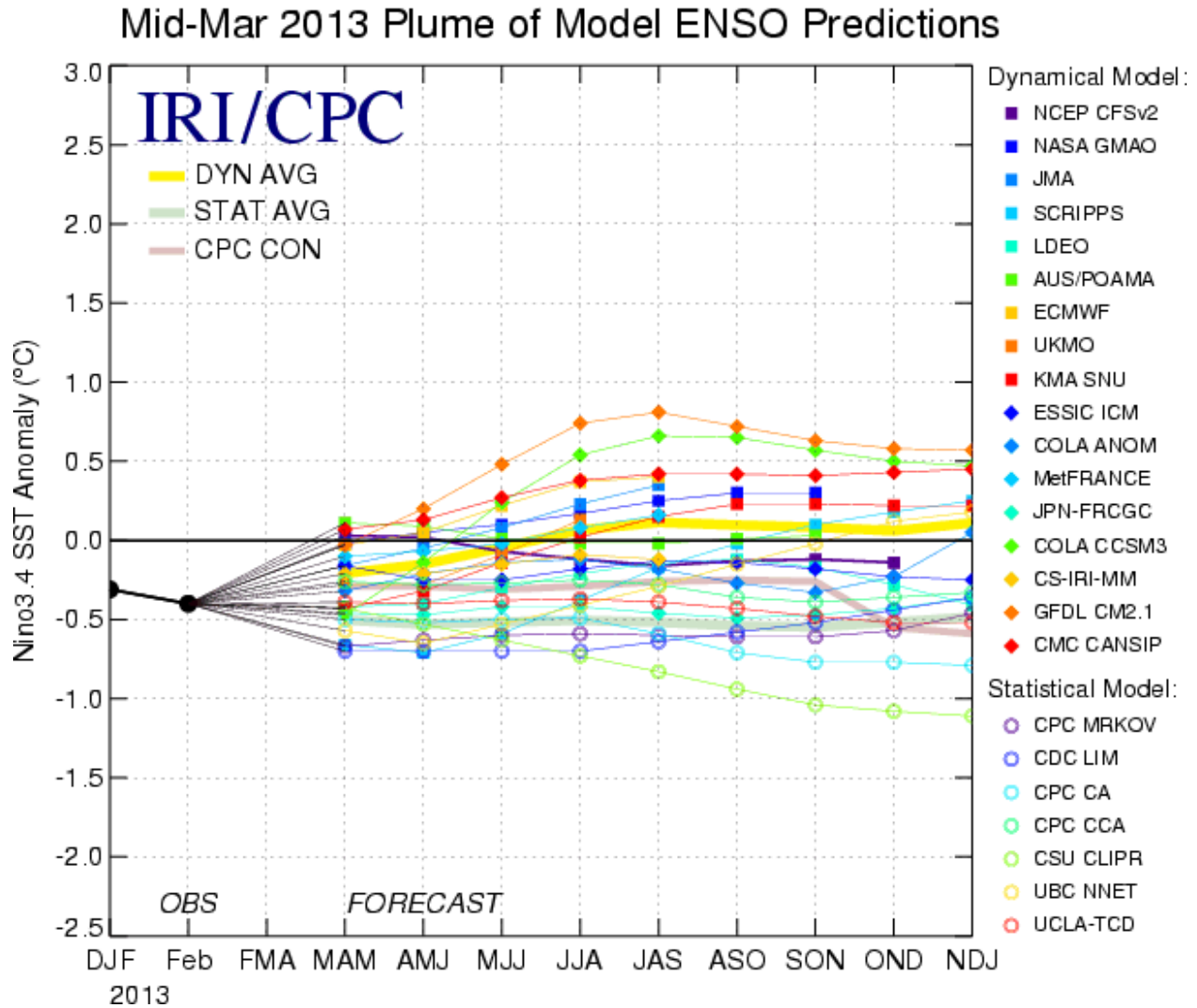

Figure 5: Example of IRI's collected forecasts - March 2013

The work presented here links those 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.

2.5.1 Modeling the link between forecasts and SSTs

IRI provides Nino 3.4 SST forecasts are over 3 month rolling windows. However, that format is unlikely to satisfy hedgers. Many would prefer to mix and match the months closest to them. Existing El Niño insurance is based on a Novermber/December average, but some clients in Peru expressed interest in protection against individual months.

So, for the sake of providing ENSO pricing information of most direct relevance to likely traded markets, we have linked the smoothed IRI forecasts to monthly measured SST. For an example of how we made this link, imagine that it is March and a hedger is 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 for the sake of simplicity in this section we use as the independent variable the average of IRI model averages covering October.

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.

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

Those regressions, specified in equation 1, are a simplified version of a procedure that climate scientists and statisticians have recently used to merge ENSO forecastsLuo et al. (2007)Coelho et al. (2004). 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.

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

---

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

2.5.2 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-upStan 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	25th q	50th q	75th q	97.5^{th} q	n_eff	Rhat
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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
\multicolumn{9}{c}{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 8, 9, 10, and 11.

For the sake of clarity, simplified illustrative examples of those figures are are presented in 6 and 7.

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 8, 9, 10, and 11. 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 8, 9, 10, and 11 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 8, 9, 10, and 11), 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 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].

2.5.3   Result 1

stochastic catalog

2.5.4   Result 2

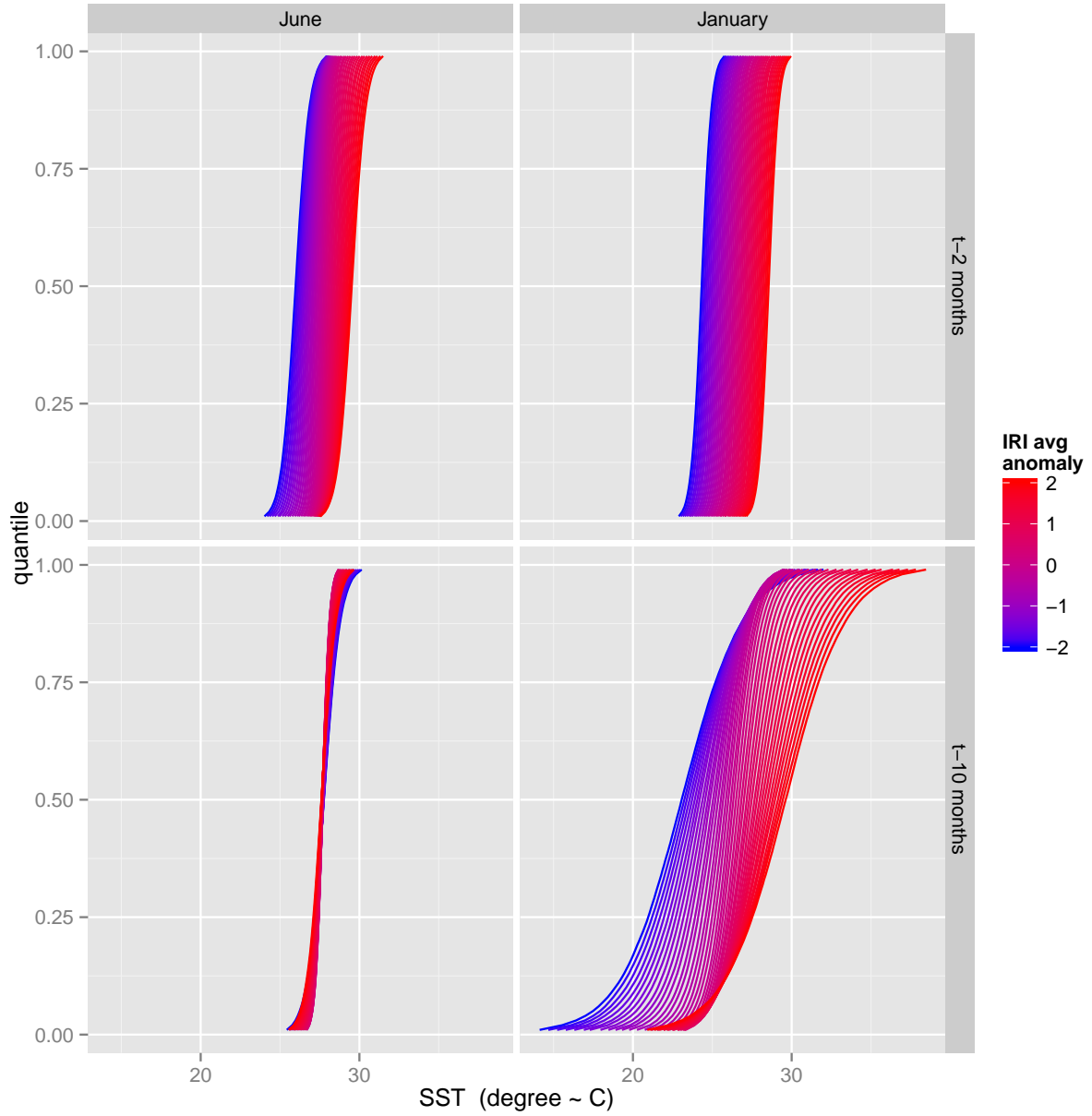Information is more important at some points than others

Figure 6: Empirical cumulative distribution functions for June and January Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. Only the ECDFs for the nearest and furthest month predictions provided by IRI are shown. ECDFs are of draws from the posterior predictive distribution of the model specified in equation 1.
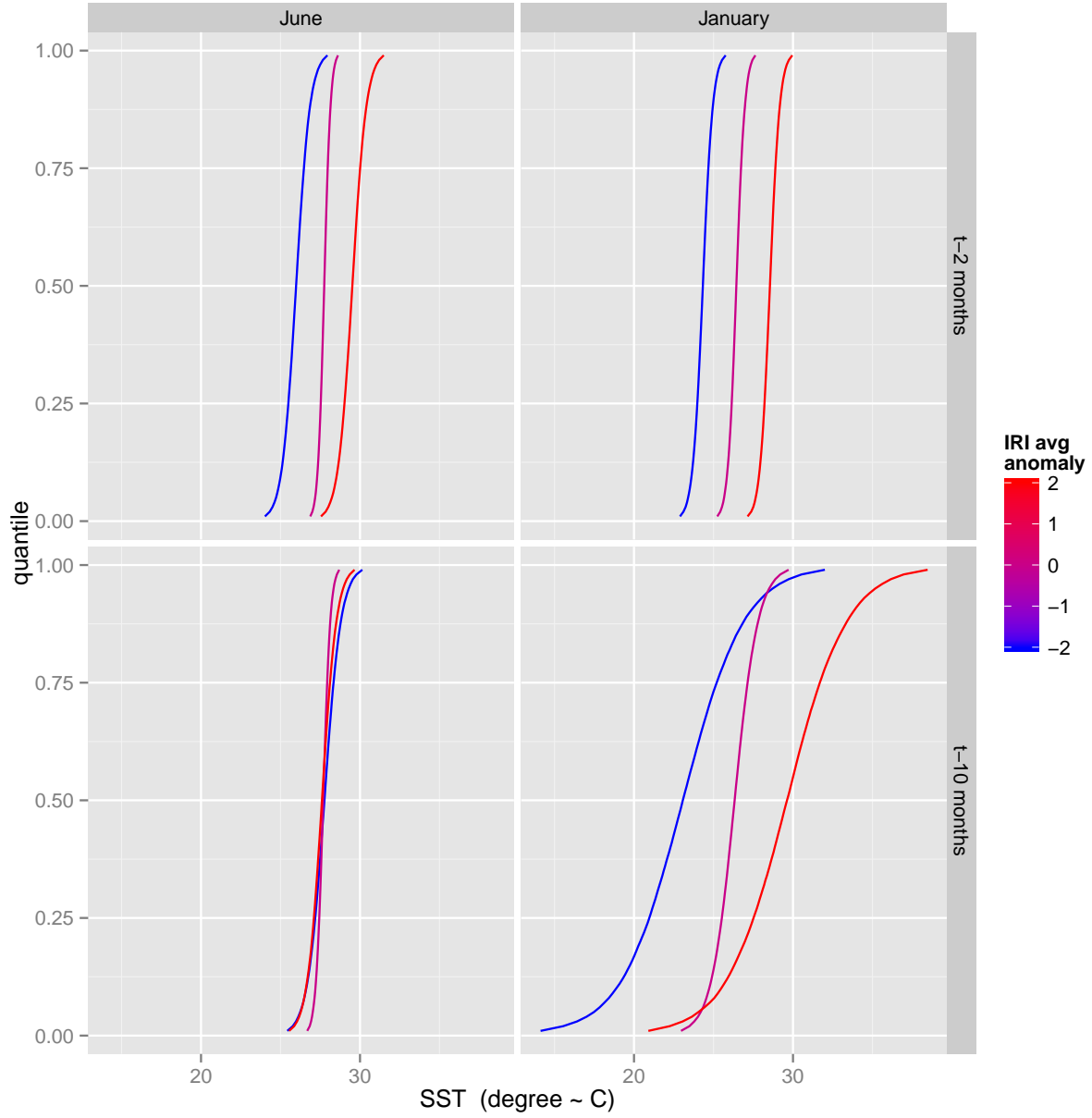
Figure 7: Empirical cumulative distribution functions for June and January Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. Only the ECDFs for the nearest and furthest month predictions provided by IRI and only predictions of large El Niño (+2), La Niña (-2), or neutral conditions (0) are shown. ECDFs are of draws from the posterior predictive distribution of the model specified in equation 1.
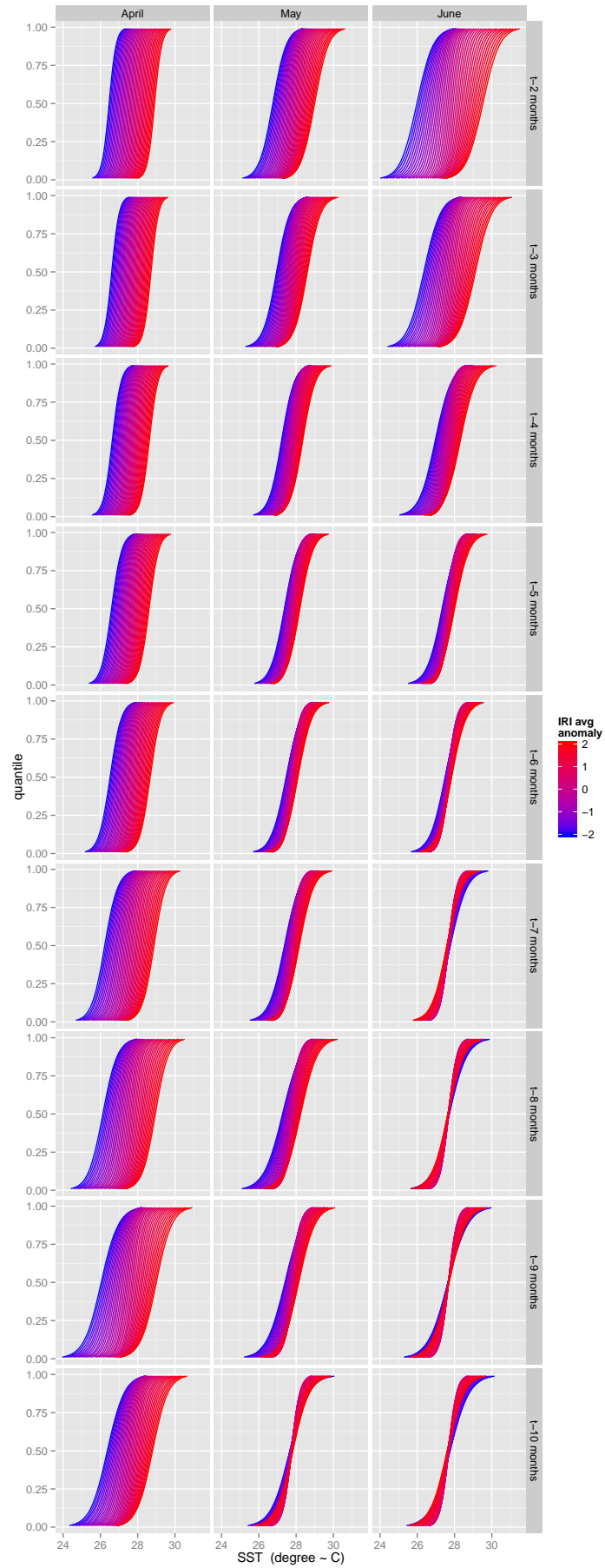
Figure 8: Empirical cumulative distribution functions for April through June Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the posterior
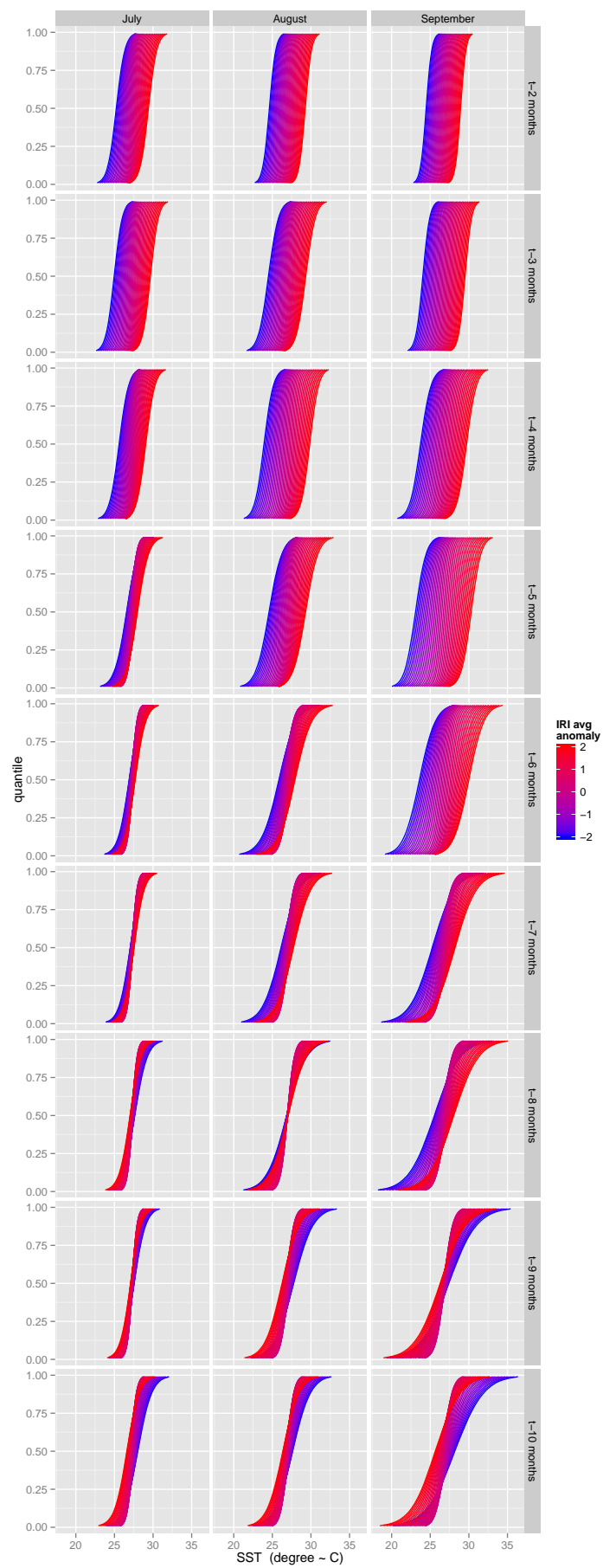
Figure 9: Empirical cumulative distribution functions for July through September Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the posterior
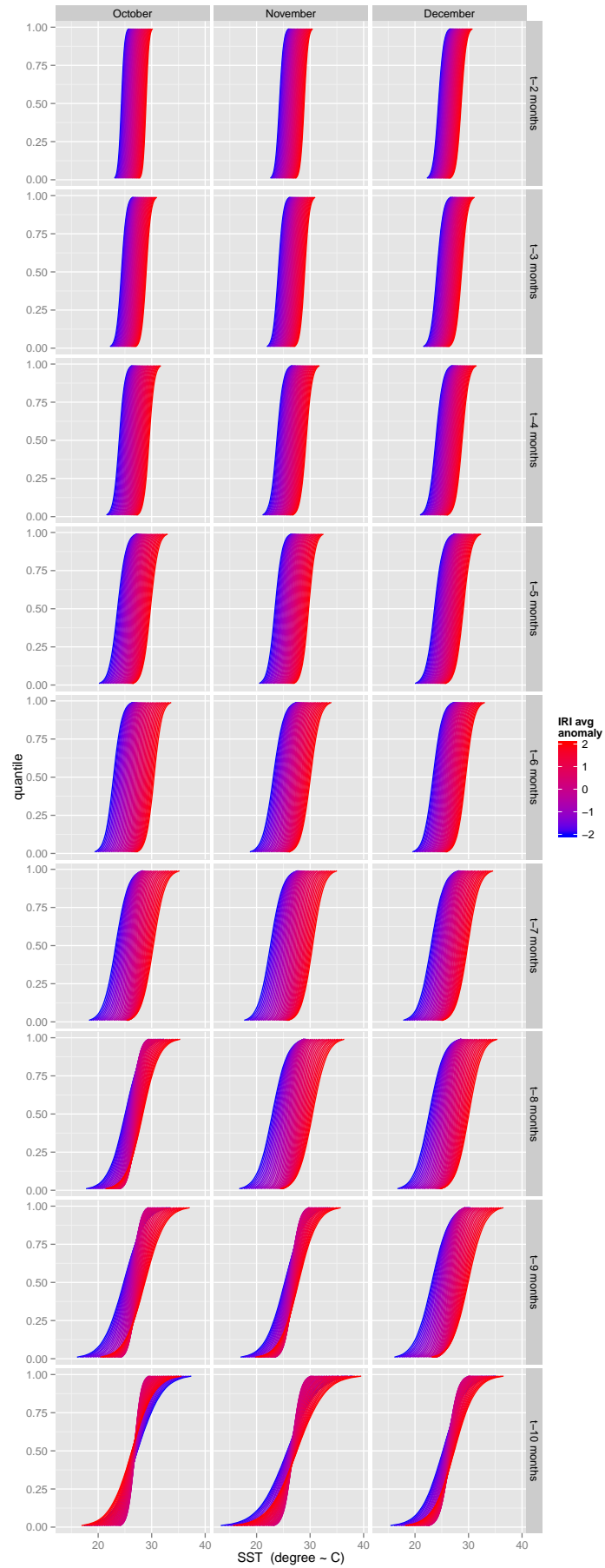
Figure 10: Empirical cumulative distribution functions for October through December Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the
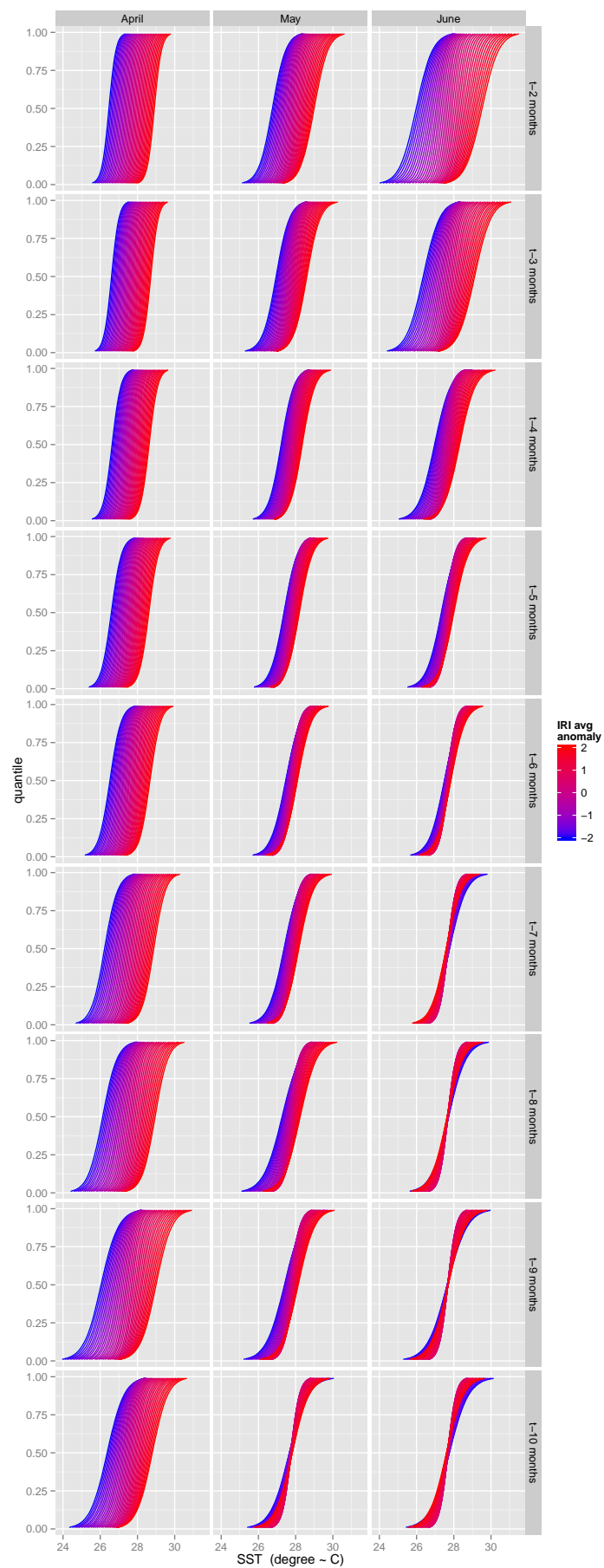
Figure 11: Empirical cumulative distribution functions for January through March Niño 3.4 SST conditioned

IRI anom	price per USD	E[SST]	2.5^{th} q	25th q	50th q	75th 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

3 Application

3.1 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

---

[4]Margining refers to the process of setting aside collateral on financial trades. On exchange-traded derivatives there are

- adjusted (upward) to allow for some reasonable expected profit for speculators.

3.2 Understanding informational and monetary gains from better forecasts

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

3.4 Alternatively: application of finding natural swaps

4 Conclusion

4.1 Key results summary

4.1.1 Distributional properties several assumptions seem to work

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

4.1.2 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

4.2 Other necessary conditions for traded market

4.3 Positive externalities

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

4.3.2 Should government finance the startup?

References

Ashok, K., Behera, S. K., Rao, S. A., Weng, H. and Yamagata, T. (2007). El Niño Modoki and its possible teleconnection, *Journal of Geophysical Research: Oceans (1978–2012)* **112**(C11).

Barnston, A., Chelliah, M. and Goldenberg, S. (1997). Documentation of a highly ENSO-related SST region in the equatorial Pacific, *Atmosphere Ocean* **35**(3): 367.

Black, D. and of Business Administration. Salomon Brothers Center for the Study of Financial Institutions, N. Y. U. G. S. (1986). Success and failure of futures contracts: Theory and empirical evidence, *New York*
.

Brorsen, B., Fofana, N. et al. (2001). Success and failure of agricultural futures contracts, *Journal of Agribusiness* **19**(2): 129–146.

Carlton, D. (1984). Futures markets: Their purpose, their history, their growth, their successes and failures, *Journal of Futures Markets* **4**(3): 237–271.

---

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.

Coelho, C., Pezzulli, S., Balmaseda, M., Doblas-Reyes, F. and StephENSOn, D. (2004). Forecast calibration and combination: A simple Bayesian approach for ENSO, *Journal of Climate* **17**(7): 1504–1516.

Copeland, T. E. and Galai, D. (1983). Information effects on the bid-ask spread, *Journal of Finance* **38**(5): 1457–1469.

Duffie, D. and Jackson, M. (1989). Optimal innovation of futures contracts, *Review of Financial Studies* **2**(3): 275–296.

Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* **14**(1): 71–100.

Gorham, M. and Kundu, P. (2012). A half-century of product innovation and competition at U.S. futures exchanges, *The Review of Futures Markets* **20**: 105–140.

I, I. W. G. (2013). Fifth assessment report, climate change 2013: The physical science basis, *Technical report*, Intergovernmental Panel on Climate Change.

Jacquet, J., Hagel, K., Hauert, C., Marotzke, J., Röhl, T. and Milinski, M. (2013). Intra-and intergenerational discounting in the climate game, *Nature Climate Change* .

Khalil, A., Kwon, H., Lall, U., Miranda, M. and Skees, J. (2007). El Niño-Southern Oscillation-based index insurance for floods: Statistical risk analyses and application to Peru, *Water Resources Research* **43**(10): 10416.

Kurtov, A. (ed.) (2010). *Investing in Insurance Risk: Insurance-Linked Securities - A Practitioner's Perspective*, Risk Books.

Kyle, A. S. (1985). Continuous auctions and insider trading, *Econometrica: Journal of the Econometric Society* pp. 1315–1335.

Leland, H. E. (1992). Insider trading: Should it be prohibited?, *Journal of Political Economy* pp. 859–887.

Luo, L., Wood, E. F. and Pan, M. (2007). Bayesian merging of multiple climate model forecasts for seasonal hydrological predictions, *Journal of Geophysical Research: Atmospheres* **112**(D10).

Nordhaus, W. (2013). *The Climate Casino*, Yale University Press.

Pennings, J. and Leuthold, R. (1999). Commodity futures contract viability: A multidisciplinary approach, *Technical report*, University of Illinois, Champagne-Urbana.

Pennings, J. and Leuthold, R. (2001). A behavioural approach towards futures contract usage, *Australian Economic Papers* **40**(4): 461–478.

Pennings, J. M. and Leuthold, R. M. (2000). The motivation for hedging revisited, *Journal of Futures Markets* **20**(9): 865–885.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us?, *Technical report*, National Bureau of Economic Research.

Reynolds, R. W. (1988). A real-time global sea surface temperature analysis, *Journal of Climate* **1**(1): 75–86.

Reynolds, R. W. and Marsico, D. C. (1993). An improved real-time global sea surface temperature analysis, *Journal of Climate* **6**(1): 114–119.

Reynolds, R. W., Rayner, N. A., Smith, T. M., Stokes, D. C. and Wang, W. (2002). An improved in situ and satellite SST analysis for climate, *Journal of Climate* **15**(13): 1609–1625.

Reynolds, R. W. and Smith, T. M. (1994). Improved global sea surface temperature analyses using optimum interpolation, *Journal of Climate* **7**(6): 929–948.

Ropelewski, C. and Halpert, M. (1987). Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation, *Mon. Wea. Rev* **115**(8): 1606–1626.

Ropelewski, C. and Halpert, M. (1989). Precipitation patterns associated with the high index phase of the Southern Oscillation., *Journal of Climate* **2**: 268–284.

Sandor, R. (2012). *Good Derivatives: A Story of Financial and Environmental Innovation*, John Wiley and Sons.

Silber, W. (1981). Innovation, competition, and new contract design in futures markets, *Journal of Futures Markets* **1**(2): 123–155.

Skees, J. and Murphy, A. (2009). ENSO Business Interruption Index Insurance for catastrophic flooding in Piura, Peru. GlobalAgRisk, Inc.

Smith, T. M. and Reynolds, R. W. (2003). Extended reconstruction of global sea surface temperatures based on COADS data (1854-1997), *Journal of Climate* **16**(10): 1495–1510.

Smith, T. M. and Reynolds, R. W. (2004). Improved extended reconstruction of SST (1854-1997), *Journal of Climate* **17**(12): 2466–2477.

Smith, T. M., Reynolds, R. W., Peterson, T. C. and Lawrimore, J. (2008). Improvements to NOAA's historical merged land-ocean surface temperature analysis (1880-2006), *Journal of Climate* **21**(10): 2283–2296.

Stan Development Team (2013). Stan: A C++ library for probability and sampling, version 1.3.
URL: *http://mc-stan.org/*

Tashjian, E. (1995). Optimal futures contract design, *The Quarterly Review of Economics and Finance* **35**(2): 153–162.

The Economist (2013). Carbon trading: Ets, rip?, *The Economist* .

Working, H. (1953). Futures trading and hedging, *The American Economic Review* **43**(3): 314–343.

Xue, Y., Smith, T. M. and Reynolds, R. W. (2003). Interdecadal changes of 30-yr SST normals during 1871-2000, *Journal of Climate* **16**(10): 1601–1612.