Pricing ENSO Derivatives

1 Introduction

1 page summary

- 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
- 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

Scope of paper and roadmap
While we start from broad scope of risk transfer, the paper's primary focus is traded derivatives [and similar comments, as needed].

1.1 The challenge of financial risk transfer for climate change

Adaptation to anthropogenic climate change remains one of the greatest challenges of the 21st century [cite]. Risks of greatest concern include increasing temperatures, dramatic precipitation changes, and rising sea levels. Those most at risk are in developing economies least equipped to adapt. Broad recognition exists of the need for financial mechanisms such as insurance as an important component of adaptation [cite UNFCCC]; however, the nature of climate change limits opportunities for financial risk transfer.

First, there is a mismatch between the time horizon of climate change and the time horizons of the the risk management tools, otherwise well suited to climate change risk. Climate risk cannot be pooled. [Add a sentence contrasting car insurance vs. earthquakes and why the latter has to go to reinsurance markets.] That means that it is not appropriate for insurance markets and must go to reinsurance, derivatives, or related risk instruments like catastrophe bonds. 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.] So the process of climate change will play out over time horizons that are too long for many commercial and public decision makers. Climate models tend to be based on 50 or even 100 year horizons [see, CITE a few]. But a risk that come to fruition over decades is difficult to translate into the short-term consequences that motivate hedging and too long for firms selling hedges to dedicate large pools of risk capital.

Second, financial risk transfer is not suitable for managing known outcomes. It is only appropriate for managing the risk around uncertain outcomes. Unfortunately, steady trends have emerged in many of the indexes that have come to define climate change.For example, the IPCC (2013) notes with virtual certainty (a >99% chance) that sea level rise will continue beyond 2100. Thus, the known outcome of sea level rise is best managed through risk mitigation (building levees, relocating populations, etc.), not risk transfer. The extent of sea level rise is uncertain – the IPCC (2013) predicts with medium confidence that sea level rise between 0.26-0.82 meters by 2100 is likely (a >66% chance) – making *extent* of sea level rise a more suitable financial hedge; however, the long time horizon precludes the development of this market.

Third, new information about climate risk is difficult to verify and integrate with previous information. The IPCC provides an important service in distilling a massive body of literature for decision makers, using the most qualified scientists in the world; however, the validity of many of their predictions often cannot be tested in our lifetime. This differs starkly from models that can be tested and improved with ongoing feedback. As a result, the capacity to use climate models for estimating and pricing uncertain outcomes associated with climate change is limited.

Fourth, parties wanting to transfer climate change risk may have difficulty identifying counterparties willing to take it. Derivatives on traded markets require balanced hedging. That generally means that market participants who would be negatively affected by an outcome need to identify and trade with those who would be positively affected. [Insert some citations from dissertation] While some individuals and industries will benefit from climate change [CITE], their economic interests pale in comparison to those that will be negatively affected. Reinsurers specialize in risks for which there is no upside, but given their current massive exposure to climate change risk and limited ability to diversify events affecting the whole world, their desire to take on additional climate change risk is likely limited.

1.1.1 Limitations of current weather markets for climate change adaptation

[Need to cut this section substantially. The only point we NEED to make here is Weather markets exist but they are low liquidity and they do not represent climate, limited as they are to temps in major cities.] Today, firms and individuals primary tools for managing risk related to extreme weather are property, crop, and business interruption insurances. [Sentence about the limitations of traditional insurance products managing this risk indirectly.] However, a variety of new weather products are protecting directly against the occurrence of adverse weather, creating new opportunities for risk transfer. For example, farmers from regions diverse as India, Malawi, Ghana, Thailand, and Canada can purchase parametric insurance which pays based on insufficient or excess rainfall [CITE].

There are also traded markets for key weather variables such as rainfall or surface temperature. The launch of these markets coincided with the deregulation of the U.S. energy sector in the late 1990s, creating a demand for energy suppliers to hedge against seasonal temperatures that would reduce their revenues (e.g., cold summers) [CITE?]. These contracts enjoyed some initial success on derivatives exchanges, but volumes have declined in recent years. While some of that declining volume has been offset by over-the-counter trading, which does not factor into official volume statistics, industry experts believe that the general trend has been toward less active trading.

What exchange trading of weather derivative there is, focuses on temperatures in major cities. (Currently, the Chicago Mercantile Exchange includes temperatures contracts for major cities in the U.S., Canada, Europe, Japan, and Australia as well as derivatives for hurricanes, snowfall, and rainfall in vulnerable U.S. cities.) That focus stems from a need to balance basis risk and standardization. Only temperatures in a few large cities translate well enough into tangible business risks for a self-sustaining volume of trades to occur.

The fact that those markets are so localized means that they miss the chance to a) clearly represent changes to the climate as they unfold over regional or global geographic scales, and b) to attract participation from the diverse groups of hedgers adversely affected by those interlinked patterns of changing weather.

While there are no theoretical barriers to very long-dated weather derivatives or (re)insurance, in practice few if any of these products provide coverage for more than one year. While the incremental change in weather risk due to climate change from one year to the next is small, these changes can be integrated in the price of contracts. For example, reinsurers often include an "uncertainty load," additional premium for risks they believe may differ from the historical record.

While the risks that climate models predict 50 to 100 years in the future are likely too far away for financial hedging, many public and private decision makers have planning horizons that extend beyond one year and so would benefit from protection of longer duration than that typically provided by weather insurance and derivatives. Adaptation to climate change frequently requires multiyear investments. For example, the government of Moazambique is making short- and long-term investments improving dykes, levees, and dams to adapt to increasing flood risk in the Limpopo River Basin (Bank; 2013). Also, consider a large agricultural producer wanting to manage its financial risk while switching farming systems in response to changing growing conditions. [Would be great if we can find real life examples of this] These and other decision makers would potentially benefit from financial protection to complement these investments and may be in particular need during this adaptation process.

Together, the difficulties of building meaningful financial contracts directly around climate change and the short comings of managing climate risk with existing weather markets suggest a missing market, one that could cover more than short-term weather, meet the necessary conditions for financial transfer outlined above, and fit within the planning horizons of decision makers attempting to prepare for a changing climate. This paper considers whether financial markets for index of what climate scientists call "teleconnections" might address that market gap.

1.1.2 The potential of financial markets for teleconnections

[Need to slash this section. Refer people elsewhere if they want more information on what teleconnections are.] Teleconnections are statistical and physical links between regional oceanic/atmospheric anomalies (most often atmospheric pressure and the flow of air and ocean currents) and patterns of catastrophic weather around the world.

The most vivid example of teleconnections come from the El Niño Southern Oscillation (ENSO). Extreme anomalies in the the ENSO system (known as El Niño and La Niña events) are regional phenonmenon with global impacts. 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].

Other important regional climate anomalies with teleconnections include the Arctic Oscillation (AO), which affects winter conditions in many areas of the northern hemisphere, the Quasi-biennial Oscillation (QBO), which appears to influence hurricanes, winter temperature extremes in the Northern hemisphere, and Indian monsoons, and the Indian Ocean Dipole, which influences the monsoon season in India and rainfall in Australia and Southeast Asia [CITE and verify any and all of these].

The climate anomalies underlying teleconnections have time scaling varying from weeks to decades. [[Examples of different time frames]

Each year, ENSO experiences seasonal periods of warming and cooling....[tell more about ENSO and annual and multiyear footprints]]

Because of its relative importance, this paper uses ENSO as a test example for evaluating the potential of a traded financial market. ENSO has a warming anomaly called El Niño, which occurs due to disruptions in ocean and atmospheric circulation across the equatorial Pacific. The changing pressure affects the formation of weather fronts throughout the world. La Niña is a cooling event above normal circulation in the Pacific. While La Niña tends to affect as many regions as El Niño, its consequences are not as acute.

The influence of anthropogenic climate change on ENSO has been studied a great deal with conflicting results [e.g., CITE]. Recent evidence, such as from [CITE] finds that climate change is likely to increase the frequency of severe ENSO anomalies. The IPCC (2013) concludes ENSO related rainfall is *likely* to intensify due to climate change.

Another aspect of teleconnections that increases the value of hedging against their extremes is that their anomalies predate regional weather conditions by weeks and sometimes months. For example, [provide example, preferably that isn't flooding in Peru since it will be discussed extensively below. (Instead, maybe winter weather in the U.S.?, something in Austriala? Monsoon in India?)]. A financial option could pay before on-the-ground difficulties emerged. In the context of climate change, such a contract could provide liquidity for adaptive management, adjusting production decisions based on emerging information, or for loss mitigation before a severe event. Because El Niño seems to be increasing due to climate change, the emergence of a new event may be an important moment when decision makers update their risk perceptions. Thus, an early payment from an option on El Niño would come to the hedger at a decision point in which she must decide whether to use the liquidity to reduce losses under the current production strategy or to use it to finance an adaptive change.

1.2 Economic effects of El Niño and La Niña

[As much as possible, let's reference this out as estimating total losses is beyond the scope here. We can cite Grant's dissertation but should also cite some other sources, too. We will have to defend original research so as much as possible, I suggest we cite what's already out there. Also note that the extra benefit is that much of risk is in developing and emerging economies]

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 USD 8 b 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.

1.3 Peru and El Niño insurance

No where in the world is more affected by ENSO anomalies than northern Peru and southern Ecuador. ENSO circulation follows an annual cycle. An emerging El Niño results in ocean warming beginning in the first months of the year in the western Pacific and spreads eastward as the year progresses. By January of the next year, a mass of warm, humid air reaches the coast of South America and meets the cold air descending from the Andes, causing an extended period of torrential rains and flooding in northern Peru and southern Ecuador (Lagos et al.; 2008). Rain in northern Peru during the last severe El Niño in 1998 was 40 times normal rainfall for January to May (Skees and Murphy; 2009). This event causes substantial loss of life; increases water-born illnesses; disrupts markets and supply chains; destroys homes, roads, and bridges; isolates communities, and inundates crops.

Through several development-oriented projects, funded by U.S. Aid for Internationl Development, the Bill & Melinda Gates Foundation, the United Nations Development Programme, and GIZ (a German development agency), we had the opportunity to study the insurance market in Peru and contribute conceptually to the development of El Niño insurance and its application. El Niño insurance is a form of index (or parametric) insurance; it makes payments based on a measure of the severity of an event rather than on an estimate of the losses of the policyholder. The measure used for El Niño insurance is elevations in the ocean temperature off the coast of Peru. Elevated ocean temperatures are the preferred method of estimating the severity of an El Niño and so represent a logical index for this insurance [CITE?]

The insurance takes advantage of the forecastable nature of El Niño. It makes payments using November and December ocean temperatures, which predate the severe rains and flooding that begin in January, making it one of the first forecast insurances in the world. Thus, the insurance could be used for loss mitigation and adaptation in the ways described above. Because a severe El Niño has not occurred since this market developed, no evidence is available regarding how policyholders will use the early payment.

In 2011, the insurance we designed was sold to.... La Positiva and PartnerRe BLAH BLAH BLAH. More information on that insurance is available ... [cite].

1.3.1 Challenges to El Niño insurance expansion and longevity

This emerging El Niño insurance market is noteworthy in that it is the first market to directly hedge a teleconnection and has been structured as forecast insurance. Its development suggests a greater potential to transfer teleconnection risks around the world, which may facilitate climate change adaptation, as described above. Thus, while this market does not directly trade climate change risk, it seems to be a step closer than insurance and derivative contracts focused on weather in the current season.

Unfortunately, the nature of ENSO risk challenges the stability of the El Niño insurance market. First, insurance markets benefit from stable premiums as fluctuating insurance prices increase marketing and origination costs as customers move in and out of the market. To offer El Niño insurance at a stable rate, insurers must set a sales closing date far enough in advance that forecasts are not meaningful. If the insurer sets the closing date too late, potential buyers can adversely select to insure only in years when forecasts predict an event will occur. While an insurer could theoretically price the insurance dynamically throughout the year, insurers are not well structured to do so for catastrophe coverage. A time-sensitive price would need to be quoted by the reinsurer's underwriter, communicated by the reinsurance broker, confirmed by the insurer's underwriters, communicated to the insurer's broker, and then quoted to the customer, not a quick process. As a result, El Niño insurance must be purchased one year before a potential event, purchased in January to protect against the risk of torrential rains and flooding the following January. This early sales closing limits the entities that can participate 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.

Second, insurance markets benefit from stable demand. ENSO is perceived to be guided by negative feedback so that in the year following a severe El Niño, a neutral or La Niña year is more likely. Consequently, many policyholders will exit the market in the year (or several years) following a severe event. Such fluctuations in demand are discouraging to insurers and brokers, who build their business on automatic renewals and so may be unwilling to market such a product.

[Grant Stop]

[Ben Start]

1.4 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 multiyear 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

1.4.1 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.

1.4.2 (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.

1.4.3 (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 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)

1.5 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.

1.6 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.

1.6.1 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)

1.6.2 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?

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 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

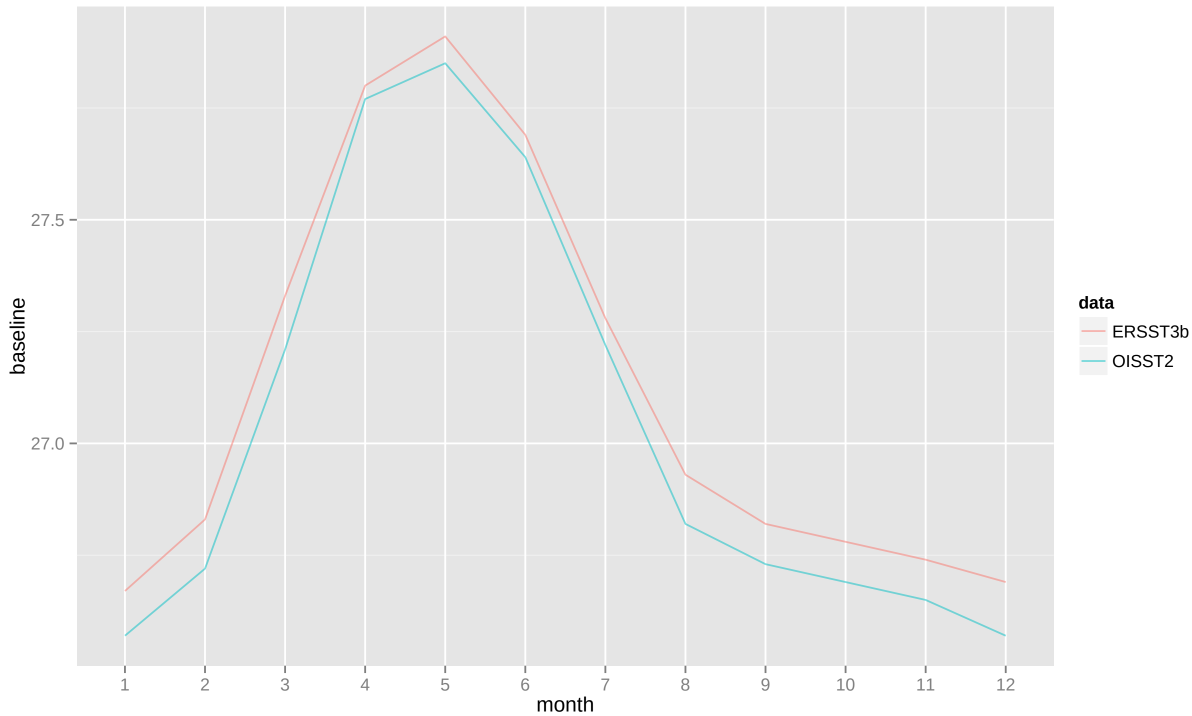

Figure 1: Comparing OISST and ERSST monthly baselines

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 PacificKhalil et al. (2007) Barnston et al. (1997). 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 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.

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

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.

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]This is also called the trigger or attachment point.

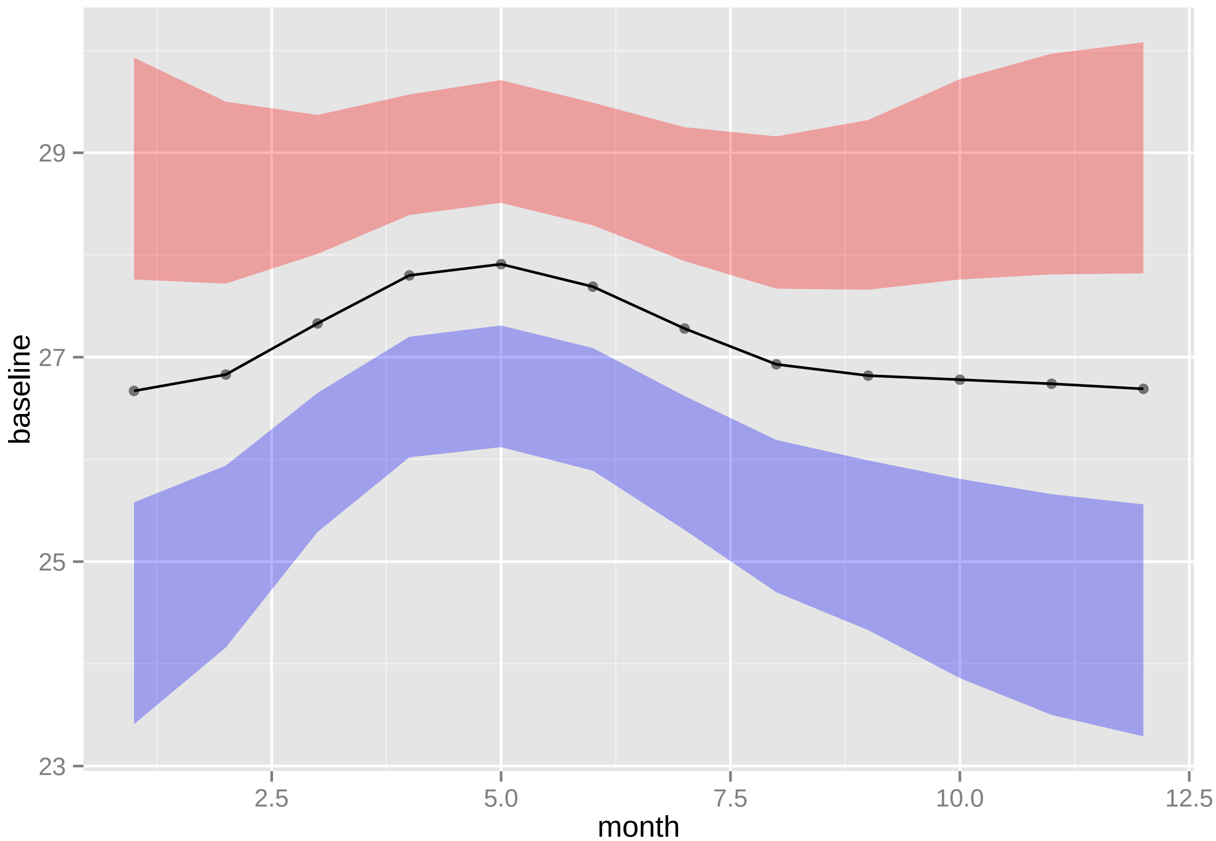

Figure 2: Index values for El Niño (red) and La Niña (blue) events between one and three standard deviations away from monthly average

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. 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

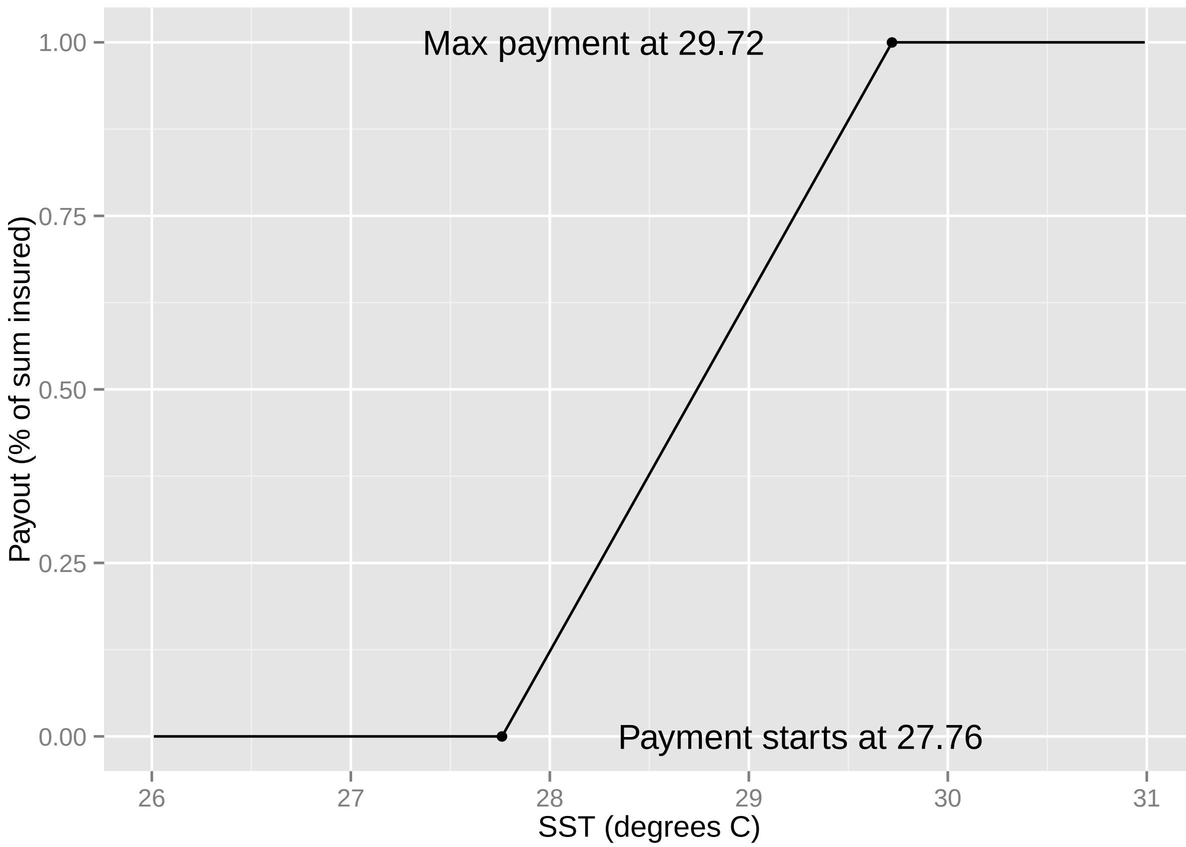

Figure 3: Payout function for call option on October SST for Niño 3.4 ERSST.3b covering index values between one and three standard deviations above the baseline

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

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.

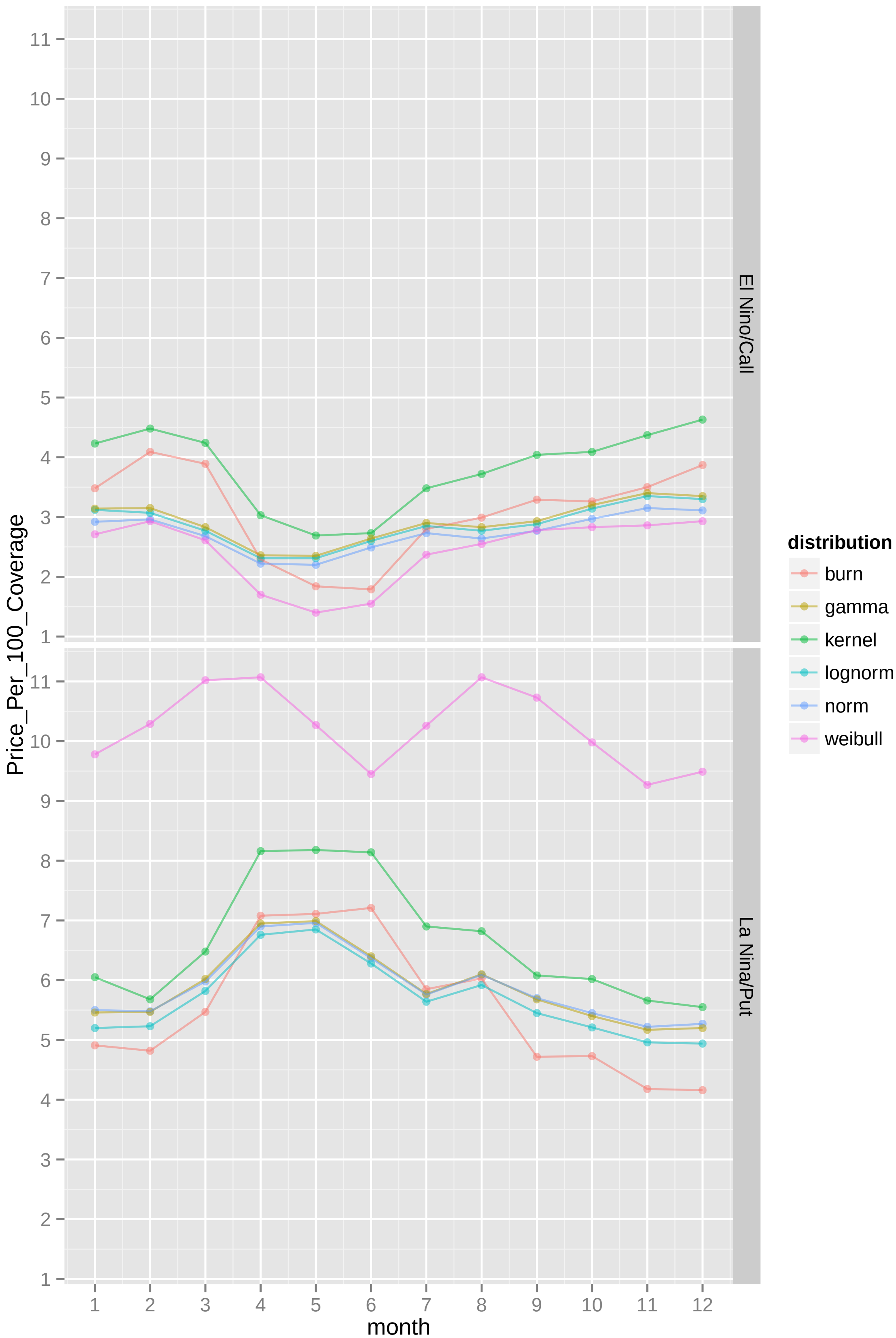

Figure 4: Expected price for options on Niño 3.4 by month, based on simulations from various distributions

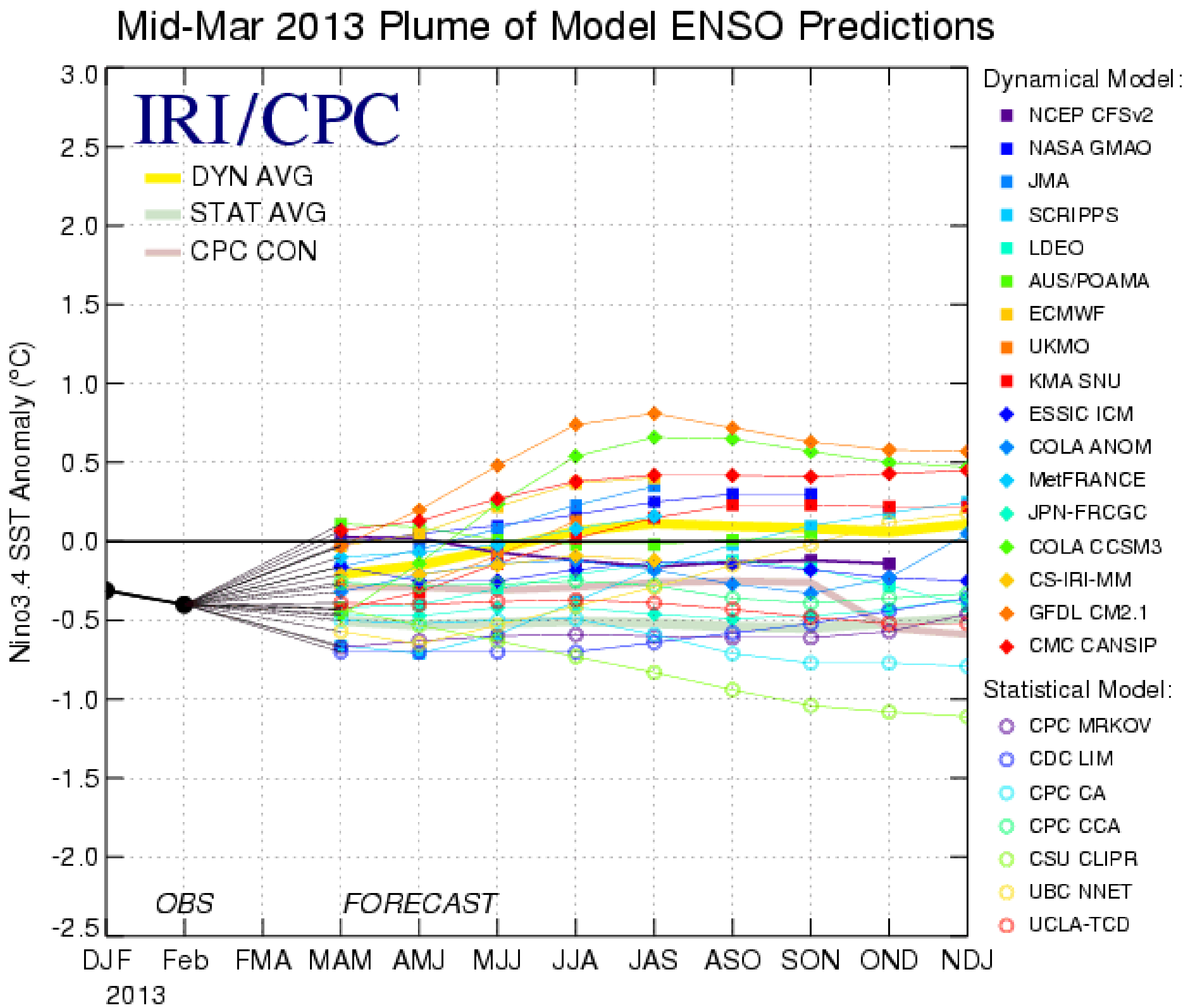

Figure 5: Example of IRI's collected forecasts - March 2013

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.

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

Those regressions, specified in equation 1, are a simplified version of a procedure that climate scientists and statisticians have recently used to merge ENSO 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.

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

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.

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

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

	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

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 **??**, **??**, **??**, and **??**.

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

In those figures, deeper blue lines indicate colder forecast averages from IRI and deeper red lines indicate

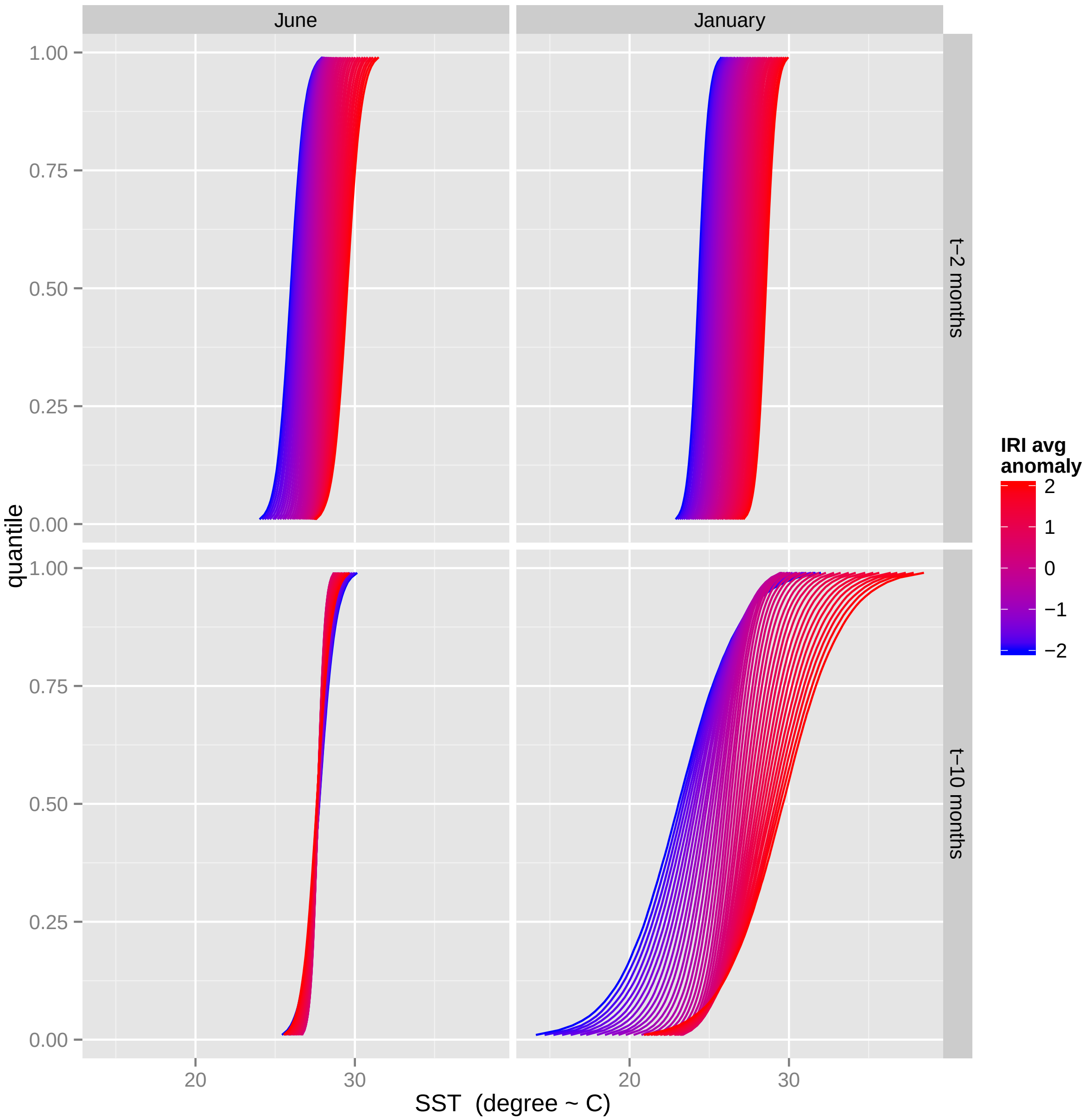

Figure 6: Empirical cumulative distribution functions for June and January Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. Only the ECDFs for the nearest and furthest month predictions provided by IRI are shown. ECDFs are of draws from the posterior predictive distribution of the model specified in equation 1.

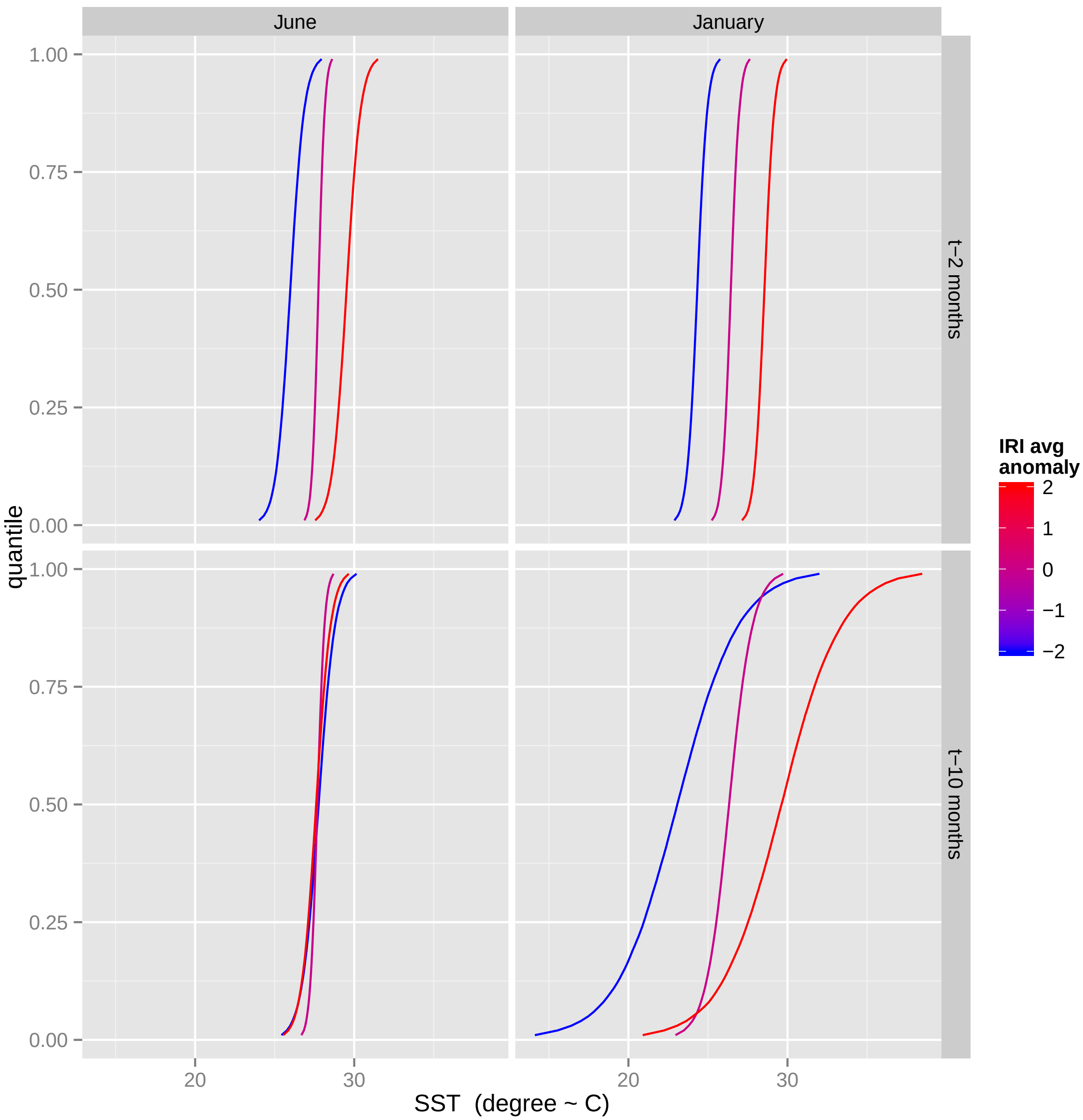

Figure 7: Empirical cumulative distribution functions for June and January Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. Only the ECDFs for the nearest and furthest month predictions provided by IRI and only predictions of large El Niño (+2), La Niña (-2), or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

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 **??**, **??**, **??**, and **??**. 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 **??**, **??**, **??**, and **??** 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 **??**, **??**, **??**, and **??**), 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

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

[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.

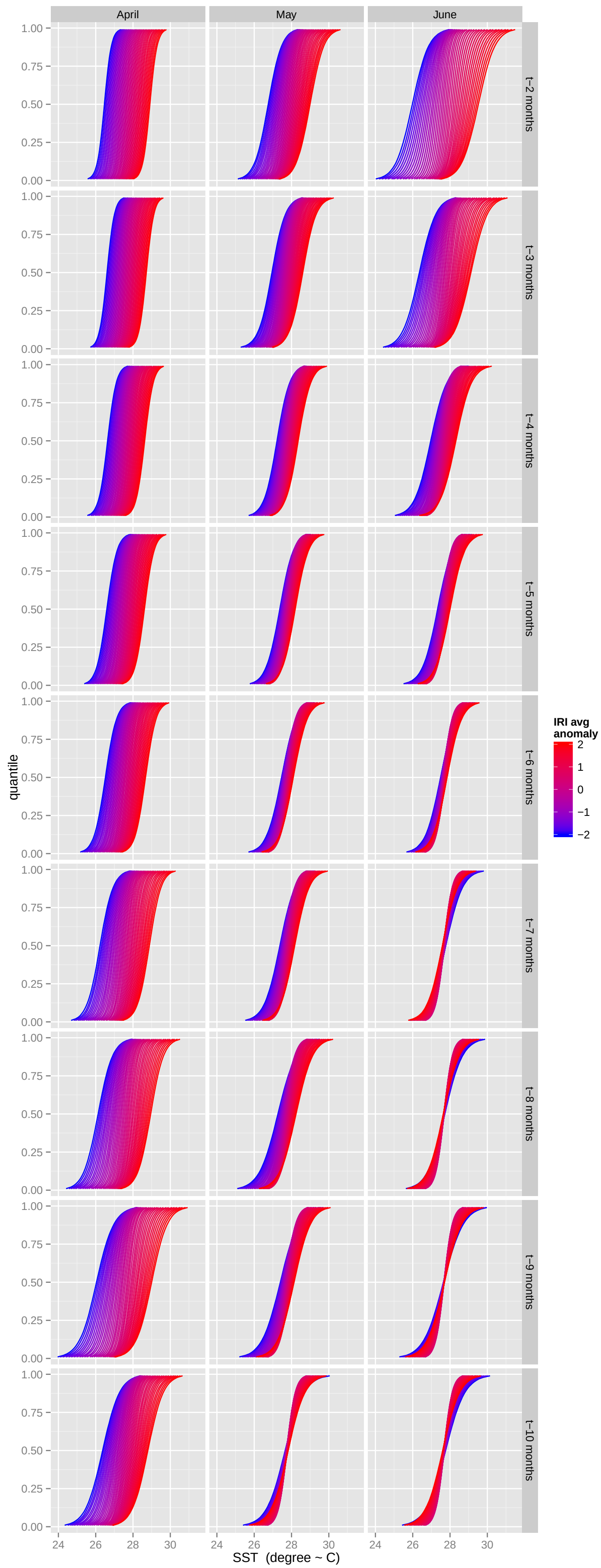

Figure 8: Empirical cumulative distribution functions for April through June Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the posterior

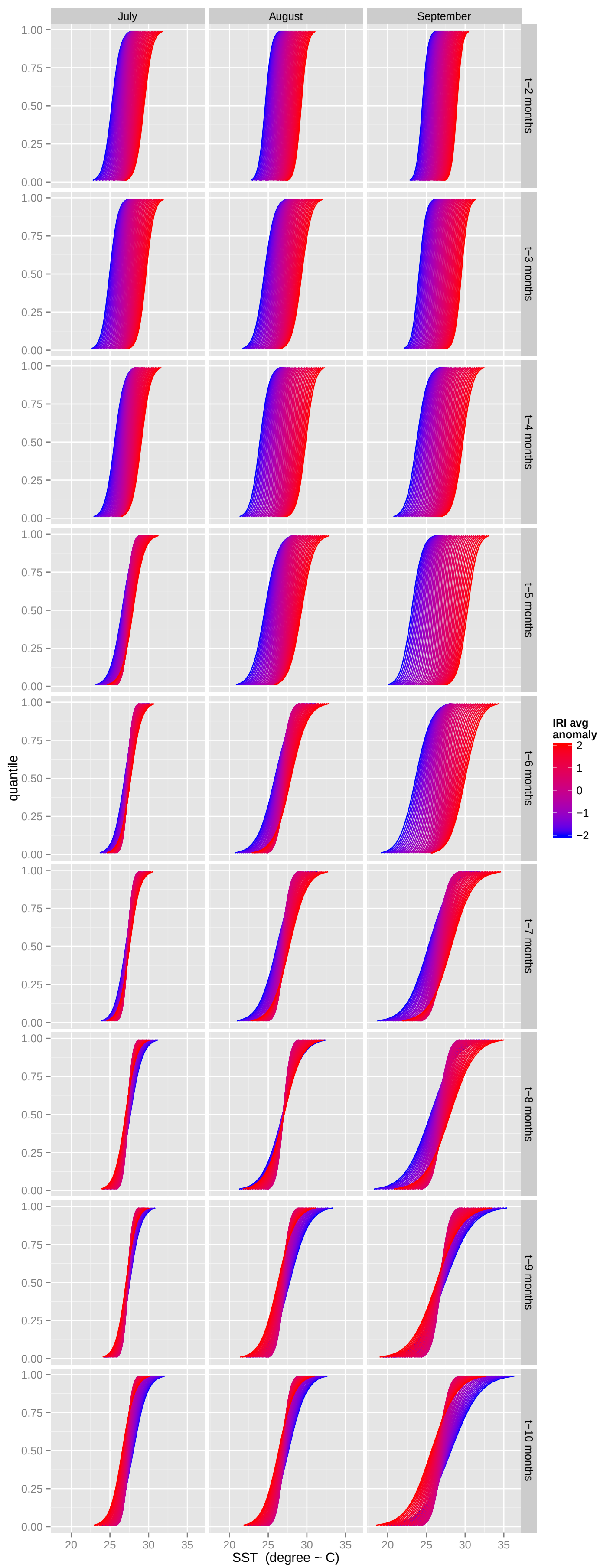

Figure 9: Empirical cumulative distribution functions for July through September Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the posterior

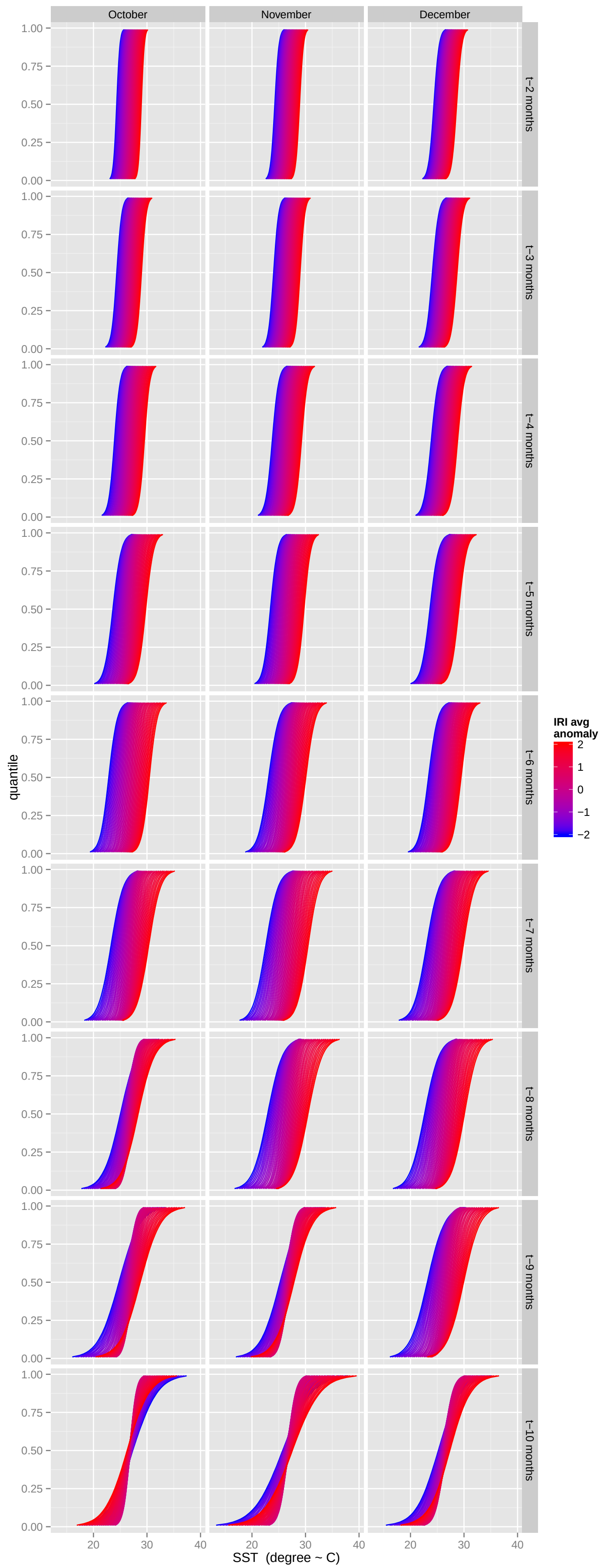

Figure 10: Empirical cumulative distribution functions for October through December Niño 3.4 SST con-
ditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the

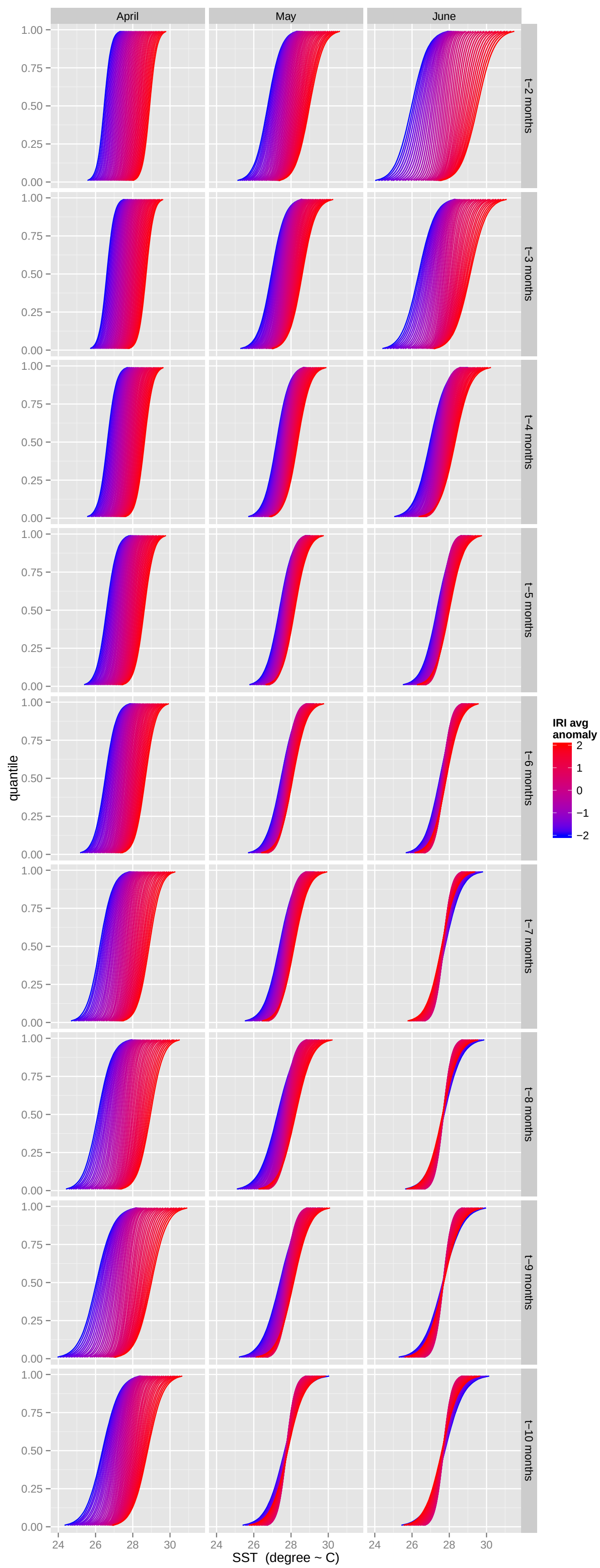

Figure 11: Empirical cumulative distribution functions for January through March Niño 3.4 SST conditioned on average IRI ensemble forecasts available for various months. ECDFs are of draws from the posterior

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

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?

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