Forecasts and Adaptation

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Abstract

For many environmental problems, economic adaptation will likely be the primary means by which potential damages are avoided. How and by how much humans adapt to environmental risks, therefore, is a question of paramount importance. This paper uses a novel dataset documenting the introduction of forecasts of an important, global driver of climate variation—El Niño/Southern Oscillation (ENSO)—to derive the first well identified estimates of total adaptation in a climate exposed industry. The primary results indicate that for the setting under consideration, risks from ENSO events can be almost entirely mitigated given 3 months of advance warning. This adaptation comes from a combination of daily and annual actions. In sum, the results point both to the ability for individuals in some settings to mitigate their own environmental risks given high quality information.
1 Introduction

For many of the most important environmental problems facing the world, Pigouvian solutions have not been forthcoming and Coasian solutions are impossible. In such cases, near-term mitigation of damages will likely occur primarily through individual actions. Thus, the question of how much and by what means individuals can adapt to environmental risks is of paramount importance. Of particular interest is how the provision of information about future risks influences the adaptation of risk-exposed agents, because such information is likely to be the only feasible environmental policy to address large environmental challenges.

Despite its importance, studies of adaptation to date have either investigated only a single adaptation mechanism (for instance Graff Zivin and Neidell (2010) and Barreca et al. (2013)) or have attempted to measure total adaptation by comparing long-term and short-term estimates (for instance Dell et al. (2009), Dell et al. (2012), and Burke and Emerick (2013)). Such studies face a challenging identification problem. I propose an alternative method based on changes in the information available to agents. Using a novel dataset of El Niño/Southern Oscillation (ENSO) forecasts and detailed data on fishing behavior in the North Pacific Ocean, I provide identified estimates of total adaptation, showing that in this setting the vast majority of ENSO impacts can potentially be adapted away. I then decompose this total response into contributions from individual adaptive behaviors.

In particular, I show that for a broad class of adaptation behaviors, cross sectional and panel estimates with observed climate variables on the right hand side and outcomes like consumption or output on the left hand side, adaptation is not identified. The intuition is that these equations both estimate impacts from the portion of climate to which the individual has not yet adapted. Moreover, both panel and cross-sectional estimates are net of adaptive behavior. Climate forecasts allow the researcher to recast the question as a typical causal inference estimation, enabling the use of program evaluation tools to assess realized and total adaptation.

Leveraging the relatively recent creation of ENSO forecasts and a long panel of
highly disaggregated data from an albacore fishery in the North Pacific Ocean, I am able to estimate total adaptation using a triple differences approach. The first treatment-control division is based on spatial heterogeneity of ENSO impacts in the North Pacific. ENSO events routinely impact the climate in certain areas of the ocean and not others, allowing me to use non-ENSO impacted vessels to control for changes in technology, biomass, and policy. Next, I divide the time series into normal and ENSO impacted periods to isolate the importance of forecasts during times when they will likely be most valuable.

Using this strategy, I find that the introduction of ENSO forecasts improve catch by more than 50% during adverse climate events, which translates to a three month adaptation rate of at least 88%. This improvement in catch represents a roughly $12 million increase in revenue for this fishery—a large amount considering the relatively small size of the fishery in question—and the amount of adaptation indicates that in this setting, potential future damages from ENSO might be minimal. This improvement in catch is robust to a wide variety of controls and alternative designations of treatment and control groups.

Finally, I examine some mechanisms by which the vessels utilize the forecasts to achieve this catch improvement. In particular, the choice of location and timing of trips are both compared between ENSO periods and non-ENSO periods as forecasts improve. Regression results indicate that climate impacted vessels use the forecasts to move eastward in response to improvements in forecasts and that these vessels start their season closer to winter. Further results highlight the importance of particular mechanisms in explaining the ability for forecasts to improve catch.

Additionally, I show that the forecasts have impact over and above individual learning, further indicating that forecasts provide information to at-risk individuals that can improve outcomes. These estimates reinforce the fact that adaptation can interact positively with policy, with directed information provision doing better than individual learning alone.

These results have important implications beyond the particular fishery in which they are based. They provide a new and robust method for estimating adaptation...
to environmental risks in a wide variety of settings. The novel dataset of ENSO forecasts can be used to assess adaptation to this particular climate process in settings outside of fisheries. Finally, the empirical results give insight into optimal climate policy. In a setting with highly mobile firms and few geographic constraints, efficient policy likely relies heavily on information provision.

The paper proceeds as follows: Section 2 gives background on albacore fishing in the North Pacific, ENSO, and ENSO forecasts and provides a conceptual model of adaptation, Section 3 discusses the data, Section 4 details the methodology for estimating adaptation, forecast value, and adaptation mechanisms, Section 5 gives the headline adaptation result, Section 6 explores adaptation mechanisms, Section C compares the contribution of forecasts to the contribution of idiosyncratic signals, and Section 7 concludes.

2 Estimating Adaptation

2.1 Previous literature

The climate impacts literature has historically overlooked adaptation either by estimating short-run impacts excluding adaptation or by estimating long-run impacts that include both adaptation and other changes like technology and policy. One strand of the literature resulting from the pioneering work of Mendelsohn et al. (1994) and extended by Schlenker et al. (2005) uses cross-sectional regressions to arrive at long-term climate impacts net of adaptation and other long-term trends.

An alternative strand including Schlenker and Roberts (2009) uses panel regressions with fixed effects and short-term fluctuations in weather to estimate weather impacts that hopefully suffer less from confounding with adaptation.

A more recent literature claims to measure adaptation by comparing the results from a “long-run” estimation based on panel or long-difference data to a panel estimate based on shorter-term weather. An overview of this approach is given in Dell et al. (2013). Recent examples of this method include Dell et al. (2012), Dell et al. (2009), and Burke and Emerick (2013). In Section 2.2, I show that the difference between these estimators does not identify adaptation. Other methods for
estimating adaptation like the time varying slopes employed by Hornbeck (2012) to examine the impact of the dust bowl do identify adaptation under an omitted variables assumption, but cannot be used to estimate potential adaptation. A recent paper by Moore and Lobell (2014) provides an intriguing method for estimating adaptation that utilizes the same intuition as the long-run/short-run methods, but avoids the primary identification problem that hinders those methods.

Studies that investigate specific adaptation strategies or mechanisms avoid the identification problem but are limited in how much adaptive response they can estimate. In particular, investigation of individual adaptation mechanisms cannot recover an estimate for the total effect of adaptation on profit or welfare. Moreover, these studies generally do not explicitly take information provision into account when estimating adaptation mechanisms. Two studies that do explicitly use the provision of information to drive adaptation, Neidell (2009) and Graff Zivin and Neidell (2009), are most similar to the methodology adopted for this study.

Also related to the present study is Rosenzweig and Udry (2013), which deals with the role of forecasts in improving farmer profits in India. The focus of Rosenzweig and Udry (2013) is on the use of forecasts as an insurance-like product. They show that farmers consistently under-invest relative to an optimum investment implied by the forecasts. In contrast to the current study, Rosenzweig and Udry do not estimate total adaptation and do not use individual microdata. Furthermore, in direct contrast to this study’s findings on the role of centralized information, they find that forecasts increase the variability of farmer outcomes.

The specific question of how useful climate forecasts are for the public in general and fisheries in particular has been discussed in the climatology and biology literature (for instance, in Pfaff et al. (1999)), but these studies have been informal and based on analyzing individual ENSO events such as the strong 1997-1998 El Niño. Murphy (1997) provides an overview of forecast valuation studies from a number of literatures. Costello et al. (1998) discusses the value of ENSO forecasts

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1See, for instance, Greenstone and Gallagher (2008), Graff Zivin et al. (2011), Deschênes and Greenstone (2011), and Barreca et al. (2013).
to salmon fisheries using a stochastic bioeconomic model. The study finds that skillful ENSO forecasts are beneficial to the fishery but that the benefits are small relative to improved fishery management. Interestingly, the study finds that most of the gains from forecast improvement come from making more skillful predictions of shorter-term ENSO events rather than from extending the prediction lead length, a point that has broad applicability to the adaptation literature but has been under-explored. In contrast to the current study, Costello et al. (1998) is focused on optimal harvest from the fishery manager’s point of view rather than the harvester’s point of view and thus does not explore adaptation by individual agents.

2.2 Identification of current approaches

Consider estimating the impact of temperature, \( w \), and other factors, \( X \), on output, \( y \). For simplicity, assume this relationship is quadratic.\(^2\)

\[
y = w\beta_1 + w^2\beta_2 + X\gamma + \varepsilon \tag{1}
\]

In the case where moderate temperatures are beneficial and extreme temperatures are harmful, one would expect \( \beta_1 > 0 \) and \( \beta_2 < 0 \). For instance, a crop like corn grows well at moderate temperatures but will be stressed by high heat and freeze if it is too cold (Schlenker and Roberts, 2009). Human productivity is highest at moderate temperatures and falls for temperatures away from optimum (Heal and Park (2013) and Graff Zivin and Neidell (2010)). In the context of this paper, albacore congregate along certain temperature gradients in the ocean but are much less abundant away from those gradients. In general, adaptation can be thought of as changes to the influence of \( w \) on \( y \). Analytically, this can appear either through changes in the magnitude of \( (\beta_1, \beta_2) \) or through the importance of \( (\beta_1, \beta_2) \) in explaining output.

I will focus on two groups of methods for estimating adaptation that have been employed in recent studies. The first method, utilized by Hornbeck (2012) in a

\(^2\)See Sections 2.3 and for a relaxation of this assumption.
non-climate setting, examines changes in the coefficients from Equation (1) by estimating an equation with time varying slopes

\[ y_{it} = \beta_1 t w_{it} + \beta_2 t w_{it}^2 + x_{it} \gamma + \epsilon_{it} \]  

(2)

Here, the coefficients on weather are allowed to vary over time, so if adaptation is reducing the impact of weather, it could manifest in smaller \( \beta \) coefficients for later time periods, indicating changes in the structural or biological equation underlying climate impacts. This method is appropriate if adaptation is driving changes in the production function, for instance in the case of agriculture and crop selection. If one crop has a higher heat tolerance than another, switching between crops will appear to be a change in the temperature-output relationship.

This method will not, however, provide correct inference on adaptation if the underlying biological equation is constant while adaptation reduces the observed variance of weather. In-place adaptation or location choice are of this type. The case of human impacts from temperature and air conditioning is particularly apt. The biological response of humans to temperature has likely remained roughly constant over the last 100 years, but many individuals now have the ability to nearly perfectly decide their temperature exposure through air conditioning. Estimation of Equation 2 using ambient air temperature will therefore indicate that \( \beta \) is the same in each time period, but the variance of estimates will increase as air conditioner adoption expands. Cases of this form will be explored more formally in Section 2.3.

A method related to Equation (2), used in Moore and Lobell (2014), is to estimate an equation of the form

\[ y_{it} = \beta_1 \bar{w}_i + \beta_2 \bar{w}_i^2 + \beta_3 (w_{it} - \bar{w}_i)^2 + X \gamma + \epsilon_{it} \]  

(3)

Where \( \beta_3 \) is the short-term impact of climate, \( \beta_1 \) and \( \beta_2 \) define the long-term relationship, and \( \bar{w} \) is average temperature. Adaptation is determined by comparing predicted output when \( \beta_3 = 0 \) to predicted output when \( \beta_3 \neq 0 \), with the intuition
being that excluding $\beta_3$ only captures the long-term, net-of-adaptation response. This method is consistent for estimating adaptation under its assumptions, because the equation is estimated with $y_{it}$ rather than an average value of output.

The second set of methods also relies on the above intuition that short run estimates will exclude adaptation while long run estimates will include it. Adaptation is estimated by comparing the coefficients from a short term equation to those from a long term equation. One particular variant of this method compares panel to cross sectional estimates. Continuing with the weather and output example, let the panel estimates be from the following equation:

$$ y_{it} = \beta_{FE1} w_{it} + \beta_{FE2} \bar{w}_{it}^2 + x_{it} \gamma_{FE} + \alpha_i + u_{it} \quad (4) $$

The long term estimate is given by a cross-sectional regression run on averages of the variables in Equation (4).

$$ \bar{y}_i = \beta_{CS1} \bar{w}_i + \beta_{CS2} \bar{w}_i^2 + \bar{x}_i \gamma_{CS} + \bar{e}_i \quad (5) $$

The claim is that adaptation is indicated by differences in $\beta$ between Equation (4) and Equation (5). In the context of the example, where temperature anomalies harm output, the claim is that adaptation is indicated by $\beta_{FE2} > \beta_{CS2}$, the reasoning being that the cross sectional estimate captures more adaptation opportunities than the fixed effects estimate.

There is an obvious issue or incompatibility with the above procedure, however, that has likely prompted subsequent studies to use a modified version of the method: if one believes that the fixed effect is necessary for consistency of $\beta$ in Equation (4), it follows that estimates from Equation (5) will be inconsistent.

In response, more recent work has compared fixed effects estimates to so called long difference estimates.$^3$ A long difference is the change in the average of a variable over some sub-sample time period. For instance, the long difference between

$^3$See, for example, Dell et al. (2012) and Burke and Emerick (2013).
time period 1 given by \( t = 1 \ldots T_1 \) and time period 2 given by \( t = (T_1 + 1) \ldots T \) is
\[
\Delta \bar{x}_i = \bar{x}_{i2} - \bar{x}_{i1} = \frac{1}{(T-T_1)} \sum_{j=T_1+1}^{T} x_{ij} - \frac{1}{T_1} \sum_{j=1}^{T_1} x_{ij}
\]

One could call this the *longest difference* since if it divides the sample in two, but in principle, any difference of average values could be substituted in the above expression. Importantly, however, the long differencing removes the \( \alpha_i \) term from Equation (4), allowing for consistent estimation even in the presence of unobservable, fixed, individual factors. The long difference estimating equation is
\[
\Delta \bar{y}_i = \beta_{1LD} \Delta \bar{w}_i + \beta_{2LD} \Delta \bar{w}^2_i + \Delta \bar{x}_i \gamma^{LD} + \Delta \bar{u}_i
\]
As above, the claim is that adaptation is represented by differences between \( \beta^{FE} \) and \( \beta^{LD} \).

In practice, however, this method cannot identify adaptation because the coefficients estimated by the two models are asymptotically equivalent, as the following straight-forward extension to the equivalence of fixed effect and first difference estimators shows. For notation, let \( z_{it} \) be the \((1 \times K)\) data vector of \( w_{it}, w_{it}^2, \) and \( x_{it} \) for individual \( i \) at time \( t \). Let \( z_i \) be \((z_{i1}, \ldots, z_{iT})\). And following Wooldridge (2010), let \( \bar{z}_{it} \) be the within transformed value for \( z_{it} \).

**Proposition 2.1.** If \( E[u_{it}|z_i, \alpha_i] = 0 \) for \( t = 1, \ldots, T \), and both \( \sum_{t=1}^{T} E[\bar{z}_{it}|z_{it}] \) and \( \sum_{t=2}^{T} E[\Delta \bar{z}_{it}|z_{it}] \) are of rank \( K \), then the estimates from Equation (4), \( \hat{\beta}^{FE} \), and the estimates from Equation (6), \( \hat{\beta}^{LD} \) are consistent for \( \beta \) from Equation (1) and are therefore asymptotically equivalent.

For a proof, see Appendix Section D. The intuition for this result can be seen in a few ways. First, fixed effect and first difference estimates are either identical or asymptotically the same depending on the size of \( T \). The long difference estimator is similar to the first difference estimator, so we might expect it to share this same property.

Second, the panel, cross sectional, and long difference estimators are all gen-
erating pooled estimates across each \( \beta_t \) in Equation (2). Thus, these regressions will neither identify the response net of adaptation nor the response without adaptation. They will capture some response net of average adaptation over the time period, where the particular amount of adaptation will depend on the timing of adaptive activities, the length of the panel, and the time period considered.

In contrast, comparing cross sectional estimates to panel estimates could potentially capture adaptation if it all occurs in the past (prior to the data). In this case, the fixed effect estimates will remove adaptation, yielding consistent estimates of the climate impacts, while the cross sectional estimates will capture adaptation to the degree that it is correlated with climate impacts. Alternatively, one could make a strong omitted variables assumption and identify adaptation by comparing values from the beginning of the dataset to values from the end. This method is, under certain conditions, equivalent to estimating Equation (2).

Below, I present an alternative method that explicitly uses changes in information available to agents to estimate adaptation. This method also has a natural timing interpretation.

### 2.3 An adaptation model

A simple model can help clarify how to identify adaptation in practice. Although many potential adaptation profiles could be considered, I will focus on continuous adaptation to a weather process through spatial choice. This matches most closely to the empirical setting below and maps easily into other continuous or repeated decision adaptation models like the extensive margin choice of whether or not to run an air conditioner. Extensive margin adaptation will be overlooked for now, but can be thought of as a first stage investment decision prior to this model.

Consider a representative firm, \( i \), maximizing output in each time period \( t \) based on how well they match their location, \( l_{it} \), to a stochastic temperature process, \( w_{it} \). Following the discussion in Section 2.2, let weather enter the production function quadratically and ignore other inputs and alternative stochastic shocks to output.
Then the objective of the firm is to maximize expected log output, \( y_{it} \)

\[
\max_{\ell_t} \mathbb{E}[y_{it}] = \mathbb{E}[\alpha w_{it} - \beta w_{it}^2]
\]

s.t. \( w_{it} = m_{l_{it}} + \varepsilon_t \)

where \( \alpha > 0 \) and \( \beta < 0 \). The constraint captures climate and weather at a given location and time. The average, location specific climate is given by \( m_{l_{it}} \). In the simplest case, shown in Figure 1, where location is one-dimensional, \( m_t \) will be negative in the northern hemisphere, indicating that average temperature falls as one moves north and rises as one moves south.\(^4\) Initially, assume that the \( m_{l_{it}} \) portion of weather is known and that that \( \varepsilon_t \) is unknown but known to be distributed \( N(0, \sigma^2_{\varepsilon}) \).

In this case, substituting the constraint and maximizing yields the optimal location choice

\[
l_{it}^* = \frac{\alpha}{2\beta m_t}
\]

which implies expected temperature and output of \( \mathbb{E}[w_t] = \alpha / 2\beta \) and \( \mathbb{E}[y_{it}] = \alpha^2 / 4\beta \). Ex post, however, the stochastic portion of weather will result in the realized output being

\[
y_{n,it} = \frac{\alpha^2}{4\beta} - \beta \varepsilon_t^2 \tag{7}
\]

Figure 1 illustrates the difference between expected and realized output in the one-dimensional case. Knowing the mean of the climate and with a symmetric loss function in weather, the individual will choose to locate at \( l^* \), expecting to experience temperature \( w^* \). If the realized temperature anomaly is high, indicated by \( w_u \), then realized output will be \( y_u \). Had the individual known that temperature

\(^4\)Linearity of \( w = f(l) \) implies a unique solution to the location choice decision and allows one to abstract from movement costs. In the case where \( w = f(l) \) is nonlinear, movement costs will lead the individual to choose the closest location that maximizes output, and all analysis will be substantively the same.
Figure 1: Location choice, weather, and output

Notes: The figure shows the optimal location choice and output given known mean of weather but no forecast of the weather anomaly.

was going to be high, he or she would have located at $l_u^*$. Note that even without any additional structure, that this is already a model of adaptation. The individual knows $m_t$ and locates in each period to maximize expected output. Even if $m_t$ were itself stochastic, so long as it was known \textit{ex ante}, then the individual would move to $l^*$. Thus, this is a model of intensive adaptation to a continuous environmental process.

This model matches the empirical setting well. There, albacore locate along temperature gradients in order to feed, so a harvester looking for fish near the correct gradient will be more likely to catch fish, while a harvester looking on either side of the gradient will be less likely to catch fish. These temperature gradients are moved by temperature fluctuations—in this case driven by ENSO.

Now, consider what happens when forecasts of $\varepsilon_t$ are introduced. In particular, assume that the individual receives one signal, $s_t$, distributed $N(\varepsilon_t, \sigma^2_{st})$. Now, the optimal location choice becomes

\[
l_{f,u}^* = \frac{\alpha - 2\beta \varepsilon_t}{2\beta m_t}
\]
where $\hat{\varepsilon}_t$ is the prediction of $\varepsilon_t$ generated by the individual after viewing the forecast. For instance, a na"ıve individual might take $\hat{\varepsilon}_t = s_t$, and a Bayesian updater would set $\hat{\varepsilon}_t = \sigma^2_s s_t / (\sigma^2_{\varepsilon} + \sigma^2_{st})$ which I define to be $k_t s_t$. For the remainder of the section, I will assume that individuals Bayesian update where it is necessary to be explicit.

Now, the realized output associated with this location choice is

$$y_{f, it} = \frac{\alpha^2}{4\beta} - \beta (\hat{\varepsilon}_t - \varepsilon_t)^2$$  \hspace{1cm} (8)

Differencing Equations (7) and (8), one can determine the change in output associated with the introduction of the forecasts

$$\Delta y_{it} = 2\beta \hat{\varepsilon}_t \varepsilon_t - \beta \hat{\varepsilon}_t^2$$  \hspace{1cm} (9)

Thus, the individual will do better when the prediction and realization are of the same sign and when $|s_t - \varepsilon_t| < |\varepsilon_t|(1 - 2/k_t)$. In expectation, this value is positive.

Figure 2: Forecasts improve expected output

Notes: The figure shows the optimal location choice and output given known mean of weather and a forecast of the weather anomaly.

Figure 2 illustrates the changes brought about by the introduction of forecasts. The firm updates their expected distribution of temperature to be the black solid
and dashed lines in the right panel. Note that in the Bayesian case, this new distribution is inside the previous distribution, shown in gray. Based on the weather prediction, the firm chooses location \( l_f^* \). If the realized temperature is again at the 95th percentile, the firm will experience a loss in output relative to the optimum given by \( y^* - y_u' \), however the loss will be smaller in expectation than the case of a 95th percentile temperature realization without forecasts.

As the figure and Equation (8) make clear, when the forecast is perfect, the vessel will always realize output \( y^* \). More generally, in a case with less-than complete adaptation, total potential adaptation to a shock of magnitude \( \varepsilon \) is given by

\[
1 - \frac{y^* - y_f}{y^* - y_n} = \frac{y_f - y_n}{y^* - y_n}
\]

conditional on \( \sigma_{st}^2 = 0 \), where \( y_f \) is output in the presence of the forecast and \( y_n \) is output without the forecast. The case where the forecast distribution is degenerate is of especial note because the result does not depend on how the individual updates their prediction of \( \varepsilon \). In the case where \( \sigma_{st}^2 > 0 \), the specific functional form underlying structural estimation will depend on the updating process, but in Section 4 I will discuss an empirical strategy that can return estimates of adaptation for any level of forecast quality.

### 2.4 Adaptation Identification Redux

The model presented in the previous section can give further insight into the identification challenges inherent in adaptation estimation. In particular, one can explore what happens when the models from Section 2.2 are run against data generated by the model. A general treatment of these further identification issues is beyond the scope of this paper, but some points are worth noting.

First, estimating Equation (1) with the temperature will be consistent even under forecast-driven adaptation changes. The identifying variation in temperature is the *residual* error after forecasts have been processed and adaptation has been undertaken. This error will still trace out the underlying biological relationship between temperature and output, since none of the adaptations have changed that
relationship. This means, however, that these estimates will not tell one anything about adaptation.

Second, although the estimates will be consistent, the precision will fall. This result occurs because the forecasts reduce the variance of $w$ experienced by each individual. For the complete adaptation case, as the forecasts become perfect, inference will become unstable because there will be little or no variation in experienced deviations in temperature. This might be a real concern for cases like the effect of temperature on performance in developed countries with high air-conditioner penetration. In this case, there is the added issue of attributing ambient temperatures to individuals who are independently setting their experienced indoor temperature.

Third, estimates using temperature anomalies, $\varepsilon_t$, without including forecasts will be biased and inconsistent. Examination of Equation (8) makes this clear. The predicted values, $\hat{\varepsilon}_t$, are correlated with $\varepsilon_t$, so failing to include them in the estimating equation will result in an omitted variables problem.

3 Data and empirical setting

Estimating adaptation requires disaggregated data combined with relevant, real-time forecasts, making the North Pacific albacore fishery uniquely suited to this study. The combination of a direct, biological relationship between ENSO and output; high quality, daily, vessel-level data; and a long time-series component allow for powerful inference. Below, I given background on and describe datasets related to the four main pieces that go into the estimation results presented in Sections 5 and 6.

3.1 ENSO

ENSO refers to a cycle of coupled fluctuations in atmospheric pressure and sea surface temperatures across the equatorial Pacific Ocean. Portions of the cycle with warmer than average sea surface temperatures are classified as El Niño and portions with cooler than average temperatures are classified as La Niña periods. On average, an El Niño events occur every 2 to 7 years and lasts between 12 and 18 months (Trenberth, 1997). Over the period studied here (1981-2010), there were
nine periods that can be characterized as El Niño events and seven periods that can be characterized as La Niña events, according to NOAA. Figure 3 gives one depiction of the El Niño-La Niña cycle based on SST anomalies in the equatorial Pacific.

Figure 3: ENSO Cycle

Notes: The ENSO cycle is represented here by the NINO3.4 index, which is the three month moving average of SST anomalies from the NINO3.4 region of the Pacific. Values above 0.5 indicate an El Niño and values below -0.5 indicate La Niña, as denoted by the red and blue shaded regions respectively. For more information on this series, see Section 3.1.

Different agencies and researchers use different definitions for when El Niño and La Niña events occur. For this study, we will follow NOAA’s definition based on a 3-month moving average of the NINO3.4 index surpassing a 0.5°C threshold. Thus, a positive 0.5° deviation, on average, for three months is classified as an El Niño and a negative 0.5° deviation, on average, for three months is classified as a La Niña. Information on the construction of this measure can be found below. ENSO events often begin in the first third of the year, gaining strength through the end of the year, before dissipating during the first few months of the following year. The time period during which ENSO events generally occur is called the “tropical year”, and before the advent of the tropical year, forecastability of an ENSO system has historically been low.

Atmospheric and ocean currents carry the ENSO signal around the world, affecting the global climate. The relationship between a climate fluctuation like ENSO
and distant temperature anomalies is termed “teleconnection” in the climatology literature. For this study, the teleconnection between a location and the ENSO cycle is determined by the lagged correlation between the ENSO event itself and weather conditions in the area. For details on how teleconnections are calculated here, see Section 4.3. The ENSO signal is strongest in the global tropics, but, importantly here, pronounced warming or cooling is also generally observed in the North Pacific Ocean. This warming occurs at a lag of 5 to 30 days from the onset of the an ENSO event as the temperature signal is carried to the North Pacific by waves and atmospheric mixing. For a review of the connection between ENSO and North Pacific SST, see Alexander et al. (2002).

3.2 ENSO forecasting

Skillful forecasts of ENSO at lead times of more than 3 months are a relatively recent invention. An early ENSO forecast based only on atmospheric modeling was published by Inoue and O’Brien (1984). Cane et al. (1986), a group of researchers at the Lamont-Doherty Earth Observatory (LDEO), published the first coupled ocean-atmosphere forecast, termed LDEO1. Both of these forecasts are dynamical meaning that they are based on a physical models of the climate system. In the late 1980s, NOAA’s Climate Prediction Center (CPC) began to produce a statistical forecast of ENSO based on Canonical Correlation Analysis (CCA).

In June 1989, the LDEO forecast began to be issued publicly in NOAA’s Climate Diagnostics Bulletin, a publication of global climate information and medium term climate forecasts. The Climate Diagnostics Bulletin incorporated additional ENSO forecasts as they were published, starting with the CCA forecast in November 1989\(^5\). Today, the Bulletin explicitly or implicitly incorporates 13 dynamical and 8 statistical ENSO forecasts. The bulletin is released each month around the 15th. See Section 3.4 and A for more information on the content of the Bulletins.

In 1992, a NOAA’s CoastWatch program began issuing forecasts of coastal SST

\(^5\)For examples of these historical Bulletins, one can see the archive going back to 1999 at the following link: \url{http://www.cpc.ncep.noaa.gov/products/CDB/CDBArchive.html/CDB_archive.shtml}
for the United States\(^6\). These forecasts incorporated the ENSO forecasts from the Climate Diagnostics Bulletin. Personal correspondence with fishermen indicates that CoastWatch forecasts and earlier NOAA forecasts were routinely posted at albacore fishing ports along the Pacific coast.

**Figure 4: Forecast skill**

![Forecast skill graph]

*Notes:* Forecast skill is indicated by the light gray lines, and the 12 month moving average of skill is given by the blue lines. Calculation of skill is discussed in Section 4.3. El Niño periods are indicated in red, and La Niña periods are indicated in blue.

New ENSO forecasts or improvements to existing forecasts have continued to be released over the last two decades. The history of the LDEO forecasts is illustrative of the development of dynamical models. Chen et al. (1995) led to the creation and release of LDEO2, which added longer data series and improved the interaction of the atmospheric and oceanic models. LDEO3 was released based on Chen et al. (1998) and eliminated some systematic biases in previous LDEO forecasts with a statistical correction. LDEO4 was released based on Chen et al. (2000) and continued to eliminate systematic model bias. The most recent version of the forecast, LDEO5, is based on Chen et al. (2004) and improves the incorporation of SST data.

ENSO forecastability has changed inter-annually due to improvements in modeling, computing power, data quality, data length, and physical changes in the ocean-atmosphere system. Barnston et al. (2012) provides an overview of changes in forecast skill over the last decade along some of these dimensions. Intra-annually,
ENSO forecastability changes based on the season and whether an El Niño or La Niña event has already developed. Once an event begins to develop, it generally lasts through the end of the tropical year. Changes in forecast skill are shown in Figure 4.

3.3 Pacific albacore

North Pacific albacore (*Thunnus alalunga*) is a highly migratory species of tuna that travels between spawning grounds on the east coast of Japan and the west coast of North America for feeding. The albacore typically follow oceanic fronts that correspond to SST between 15 and 20°C, rarely passing this temperature boundary. Laurs and Dotson (1992) provides an overview of Pacific albacore biology. The temperature preferences of albacore make them highly responsive to changes in climate. Laurs et al. (1984) provides some of the first satellite-based evidence of the Northern Pacific albacore following water color and temperature gradients. Lu et al. (1998) looked specifically at the impact of ENSO on Southern Pacific albacore. Lehodey et al. (2003) shows that Pacific albacore recruitment falls during El Niño but rises during La Niña. Other tuna also exhibit this climate sensitivity. Lehodey et al. (1997) provides a particularly detailed analysis of the impact of ENSO on tropical Pacific skipjack tuna in the western and central Pacific Ocean. The climate sensitivity of albacore leads the albacore fishery to also be climate sensitive, thus enabling climate forecasts to be potentially helpful in improving catch.

North Pacific albacore are fished internationally by vessels from multiple flag states. Historically, United States and Japanese vessels harvested the majority of Pacific albacore. Japan is still the largest harvester in the Pacific, while the U.S. share has fallen from about 25% on average from 1950 through 1990 to about 15% on average from 2000 to the present. Purse seine harvesters from Taiwan and South Korea account for the majority of the difference. The U.S. fleet, in contrast, uses either troll or pole and line to catch albacore. The fleet had total annual revenue of between 5 and 60 million dollars from 1981 to 2010, with average annual revenue

---

7 NOAA’s Albacore Research program also has a wealth of additional information: http://swfsc.noaa.gov/textblock.aspx?Division=FRD&ParentMenuId=139&id=1168.
from 2000 through 2010 of $22 million. For an overview of the U.S. West Coast albacore fishery, which is the focus of this study, see Wise (2011). Figure 7 gives a heat map of where U.S. harvesters have reported fishing over the sample period of 1981-2010.

From discussion with fishermen, the predominant methods for adapting to changes in albacore stocks are either movement into and out of the fishery or changes in fishing locations. For instance, Wise (2011) reports that harvesters have shifted fishing effort northward during the last decade in response to northward and onshore movements of albacore over this period. Similarly, during periods when the albacore school closer to shore, smaller boats are able to take part in the fishery, inducing higher participation.

3.4 Data description

The NINO3.4 index from National Oceanic and Atmospheric Administration’s (NOAA) Climate Prediction Center (CPC) gives average temperature anomalies in a rectangular region of the Pacific from 120°W-170°W longitude and 5°S-5°N latitude. Following Trenberth (1997) and NOAA, this paper uses the NINO3.4 region to classify El Niño and La Niña events. Baseline estimation uses the NOAA definition of a three month average deviation in the NINO3.4 index of at least 0.5°C for El Niño and −0.5°C for La Niña.

Historical ENSO predictions are kept by the International Research Institute (IRI) going back to 2002. NOAA’s Coastwatch program issued forecasts directly to harvesters starting in 1999, and records of these forecasts from 1999 until 2002 are available from NOAA. From 2002 onward, the Coastwatch program began repackaging the IRI forecasts for use in their information for harvesters. Forecasts for the period prior to 1999 are available through NOAA’s Climate Diagnostics Bulletin. Description of the construction of the historical forecast dataset can be found in Section A.

The data for the albacore catch consist of daily, vessel-level logbook observations of U.S. troll vessels from 1981 to 2010. All days away from port are observed, with
active fishing days versus days spent in transit to a fishing ground indicated. Vessel characteristics including length, fishing gear, and hours fishing are also observed.

The albacore fishery data includes recordings of sea surface temperature made by the vessels at the time of catch, however this information is only recorded by two-thirds of the vessels. For the baseline specifications, therefore, satellite measures of sea surface temperature will be matched to the latitude and longitude of the vessel each day. Reynolds et al. (2002) provides a daily data set of sea surface temperature at a (1/4)° spatial resolution for the study period. Reconstruction analysis of this type is recommended for use in climate studies by Auffhammer et al. (2011).

Table 1: Data summary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(number of fish)</td>
<td>4.2</td>
<td>1.3</td>
<td>177203</td>
</tr>
<tr>
<td>ln(pounds of catch)</td>
<td>6.9</td>
<td>1.3</td>
<td>129398</td>
</tr>
<tr>
<td>Latitude</td>
<td>42.6</td>
<td>4.6</td>
<td>177203</td>
</tr>
<tr>
<td>Longitude</td>
<td>226.4</td>
<td>15.7</td>
<td>177203</td>
</tr>
<tr>
<td>log(ΔSST)</td>
<td>1</td>
<td>0.5</td>
<td>132626</td>
</tr>
<tr>
<td>NINO3.4</td>
<td>0.1</td>
<td>0.7</td>
<td>177203</td>
</tr>
<tr>
<td>ENSO event</td>
<td>0.5</td>
<td>0.5</td>
<td>177203</td>
</tr>
<tr>
<td>Skill</td>
<td>0.4</td>
<td>0.3</td>
<td>177203</td>
</tr>
<tr>
<td>Vessel length (ft)</td>
<td>63</td>
<td>20.2</td>
<td>168997</td>
</tr>
<tr>
<td>Teleconnection</td>
<td>0.1</td>
<td>0.2</td>
<td>177203</td>
</tr>
<tr>
<td>Number of trips per year</td>
<td>2.4</td>
<td>1.8</td>
<td>7695</td>
</tr>
<tr>
<td>Trip length (days)</td>
<td>15.6</td>
<td>19.6</td>
<td>7683</td>
</tr>
<tr>
<td>Trip start probability</td>
<td>0.05</td>
<td>0.22</td>
<td>7695</td>
</tr>
<tr>
<td>Unique vessels</td>
<td>2135</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A summary of the main variables used in this study can be found in Table 1. The first section gives values used in daily analysis, the second section gives values from the seasonal analysis, and the final section gives the number of unique vessels. The teleconnection and skill measures are both calculated by me, and I describe the construction below in Section 4.3.
4 Estimation strategy

4.1 Estimating total adaptation

The fraction of damages adapted away is given by Equation (10) for the case where forecasts are perfectly skillful. Estimating this value poses some practical challenges, including the immediate one of finding estimable analogues of the theoretical terms. The empirical setting described above allows for a relatively easy mapping in this case. Consider ENSO events to be the weather anomalies and take ENSO forecasts as the changes in information. Formally, let \( enso \) be 1 if either an El Niño or La Niña is occurring and 0 otherwise. Let \( skill \) be the forecast skill, as describe below in Section 4.3, which ranges between 0 (a perfectly bad forecast) and 1 (a perfectly good forecast). Then, suppressing individual subscripts, total potential adaptation is given by

\[
\frac{y_f - y_n}{y^* - y_n} = \frac{E[y|skill = 1, enso = 1] - E[y|skill = 0, enso = 1]}{E[y|enso = 0] - E[y|enso = 0, skill = 1]}
\]  (11)

with the assumption being that a perfectly skillful forecast transforms the \textit{ex ante} decision into the \textit{ex post} decision, which can be proxied by the case where an ENSO event did not occur. In practice, this will mean that adaptation is always with respect to the unshocked state.

These conditional expectations are all estimable given information on output, forecast skill, and ENSO. There is one ambiguity, however, in how the \( E[y|enso = 0] \) term should be estimated. In practice, this will be an average over the different levels of observed skill, but one could imagine calculating the value at different levels of skill. Because skill is changing over time, as a baseline measure of adaptation, I will report an alternative value that provides closer temporal comparisons

\[
1 - \frac{y_f^* - y_f}{y_n^* - y_n} = 1 - \frac{E[y|skill = 1, enso = 0] - E[y|skill = 1, enso = 1]}{E[y|skill = 0, enso = 0] - E[y|enso = 1, skill = 0]}
\]  (12)

Finally, I will use teleconnection status, denoted \( tel \), to help obviate concerns with confounding changes in technology and policy. The forecasts should have more
salience for harvesters fishing in teleconnected areas, allowing me to use vessels fishing in non-teleconnected areas as a contemporaneous control group.

Putting these terms together, results in an estimation that is similar to a triple differences (DDD) specification. Forecast skill can be thought of as the policy variable, ENSO events create a time-varying treatment-control division, and teleconnection status creates a contemporaneous treatment-control division. The estimating equation includes these three variables, their second and third level interactions, and controls including individual and time fixed effects.

\[
y_{it} = \beta_0 \text{enso}_t + \beta_1 \text{tel}_{it} + \beta_2 \text{skill}_t \\
+ \delta_0 \text{tel}_{it} \text{enso}_t + \delta_1 \text{skill}_t \text{tel}_{it} + \delta_2 \text{skill}_t \text{enso}_t \\
+ \delta_3 \text{skill}_t \text{tel}_{it} \text{enso}_t + \mathbf{x}_{it} \theta + \lambda_w + \alpha_i + \epsilon_{it} \tag{13}
\]

Translating Equation (12) into coefficients from Equation (13) for the treated group, one has

\[
1 - \frac{E[y|\text{skill} = 1, \text{enso} = 0] - E[y|\text{skill} = 1, \text{enso} = 1]}{E[y|\text{skill} = 0, \text{enso} = 0] - E[y|\text{enso} = 1, \text{skill} = 0]} = \frac{\delta_3}{-\delta_0} \tag{14}
\]

Note that based on Figure 4, this is not an out-of-sample extrapolation: forecast skill does rise to 1 during some points in the sample period. One could consider this to be a lower bound, however, in that a forecast with \textit{ex post} skill of 1 is still not the same as prior knowledge that the forecast will have perfect skill. This difference can be investigated by looking at \textit{ex ante} uncertainty of the forecasts, an issue that will be pursued in future work.

If one instead wants to calculate the empirical analogue of the conditional expectation as given in Equation (11), the law of large numbers gives

\[
\frac{\hat{\delta}_1 + \hat{\delta}_3}{\hat{\delta}_1 \text{skill} - \hat{\delta}_0} \rightarrow_P \frac{E[y|\text{skill} = 1, \text{enso} = 1] - E[y|\text{skill} = 0, \text{enso} = 1]}{E[y|\text{enso} = 0] - E[y|\text{enso} = 0, \text{skill} = 1]} \tag{15}
\]

where $\text{skill}$ is the average observed skill in the dataset. Asymptotics here are in $N$. One might think that with asymptotics over $T$, skill will be 1 almost surely. This
would make the above expression unidentified, but with some abuse of notation, this value could be estimated by replacing average skill in (15) by 1. I will assume that my sample is growing in number of vessels.

The coefficients from the triple differences equation are of interest in themselves as well. The triple interaction, $\delta_3$, gives the real value of the forecast to treated vessels (teleconnected) during treatment (ENSO event). The $\delta_0$ coefficient gives the “climate impacts” of ENSO.

### 4.2 Estimating adaptation mechanisms

Estimating each adaptation mechanism is done in a similar way to estimating total adaptation. In particular, for daily location choice, I estimate Equation (13), but replace $y_{it}$ with latitude, longitude, and a function of distance from optimal sea surface temperature gradient, as described in the results section below.

For trip-level decisions, I estimate variants of Equation (13) using annual data. The most important difference is in estimating changes in trip start probabilities. There, I use the same triple interaction estimate method, but instead of breaking the time series into ENSO and normal periods, I divide time by months before or after the onset of and ENSO event. Formally let $\tau_0$ be the month that an ENSO event starts, let $\tau_j$ be the time $j$ months before ($j < 0$) or after ($j > 0$) ENSO onset, and let $m$ be the current month relative to ENSO onset. Then

$$y_{it} = \beta_{0j} \sum_j 1_{\{m=\tau_j\}} + \beta_{1\text{tel}_t} + \beta_{2\text{skill}_t}$$

$$+ \delta_{0j} \text{tel}_t \sum_j 1_{\{m=\tau_j\}} + \delta_{1\text{skill}_t} \text{tel}_t + \delta_{2j\text{skill}_t} \sum_j 1_{\{m=\tau_j\}}$$

$$+ \delta_{3j\text{skill}_t} \text{tel}_t \sum_j 1_{\{m=\tau_j\}} + x_{it} \theta + \lambda_w + \alpha_i + \varepsilon_{it} \quad (16)$$

The logic is that once skillful forecasts are released, vessels will be better able manage their ENSO-related risk, so more trips might be started after ENSO begins in this case.
4.3 Calculating teleconnections and skill

Following Hsiang et al. (2011), ENSO teleconnections—the relationship between ENSO and other locations on the globe—are created by calculating correlations between lagged values of the NINO3.4 index and SSTs in the Pacific Ocean. I have chosen a lag of one month based on the discussion in Section 3.1. More precisely, let \( m \) be the month, \( y \) the year, \( x \) the location, and \( L \) a lag length in months. Let \( NINO(m, y) \) be the NINO3.4 index value for month \( m \) in year \( y \), \( T(x, m, y) \) be the temperature at location \( x \), month \( m \), and year \( y \). Let \( \rho(x, m, L) = \text{corr}(NINO(m, y), T(x, m+L, y)) \) for all \( y \). I define teleconnection as this correlation when \( L = 1 \).

Note that Hsiang et al. (2011) performs an additional step based on summing the number of months for which this correlation is significant, then aggregating that number up to the national level. This is done by constructing an indicator function for values that are significant at the 10% level: \( \tilde{\rho}(x, m, L) = 1\{\rho(x, m, L) \text{ sig. at 10% level}\} \), letting \( M_{xL} = \sum_{m=1}^{12} \tilde{\rho}(x, m, L) \), and then setting teleconnection between ENSO and location \( x \) to be given by \( V_x(L, R) = 1\{M_{xL} \geq R\} \) for a researcher chosen value of \( R \). I do not perform this additional step because I use daily data at the pixel level rather than annual data at the national level. Moreover, I do not mask my correlation by only considering values that are significant. With a balanced panel of SST, such significance masking is purely magnitude based, so it keeps relatively extreme values. I chose to keep all values in my main analysis and explore the robustness of my results to this alternatives in additional checks.

Figure 5 shows the average output from the correlation step of the teleconnection calculation process. Red values indicating correlation near 1 and blue cells indicating values near -1. One can see from Figure 5b that the vessels observed in the dataset fish across the North Pacific. Roughly 75% of fishing observations occur in positively correlated areas, with the median correlation being 0.11 and the 75th percentile correlation being 0.21. The straight lines radiating from Hawaii, Samoa, Guam, and the Solomon Islands are from vessels steaming from their home ports to fishing grounds. I have logbook records of whether the vessel is fishing or...
steaming, and when estimating adaptation, these observations will be removed.

Forecast skill is the quality of the forecast of interest relative to another forecast. I calculate skill as follows: for the 3 month ahead forecast, I calculate the squared error for that month, \( SE_{fcst,m} = (FCST_{3,m} - \text{NINO3.4}_m)^2 \), and the squared error of a naïve forecast based on simple autoregression, \( SE_{ref,m} = (\rho \text{NINO3.4}_{m-3} - \text{NINO3.4}_m)^2 \), where \( m \) indexes the month. Skill for month \( m \) is then \( \exp(\ln(0.5) \times -SE_{fcst,m}/SE_{ref,m}) \). For the period before June 1989, forecast skill is set to 0.

5 Results for total adaptation

Table 2 implements the estimation strategy outlined in Section 4.1. The results show that improvements in forecasts are beneficial to ENSO-exposed harvesters, with the triple interaction indicating that moving from having no forecast to a perfect forecast increases catch by more than 50%. With the inclusion of controls for the strength of ENSO events (column 2), this value increases to nearly 60%. The triple interaction coefficient and the coefficient on ENSO impacts for teleconnected vessels, using the formula in Equation (14), indicate that adaptation potential is high—88% or higher in all specifications. This value means that with a perfect forecast with a three month lead, harvesters are able to adapt away up to 88%
### Table 2: Total Adaptation: Daily

<table>
<thead>
<tr>
<th></th>
<th>log(fish)</th>
<th>log(fish)</th>
<th>log(catch)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teleconnection</td>
<td>0.30***</td>
<td>0.26***</td>
<td>0.25*</td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td>(0.095)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Skill</td>
<td>0.055</td>
<td>0.056</td>
<td>0.083</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.052)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>ENSO event</td>
<td>-0.073*</td>
<td>-0.045</td>
<td>-0.068</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.039)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Tele. × skill</td>
<td>0.058</td>
<td>0.10</td>
<td>-0.26</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.18)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Tele. × ENSO</td>
<td>-0.58***</td>
<td>-0.56***</td>
<td>-0.60***</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>Skill × ENSO</td>
<td>-0.084</td>
<td>-0.093</td>
<td>-0.069</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.064)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Tele. × skill × ENSO</td>
<td>0.51**</td>
<td>0.59**</td>
<td>0.77**</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.23)</td>
<td>(0.31)</td>
</tr>
<tr>
<td>Adaptation</td>
<td>0.88***</td>
<td>1.06***</td>
<td>1.28***</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.28)</td>
<td>(0.28)</td>
</tr>
</tbody>
</table>

Year FE | Yes | Yes | Yes |
Week FE | Yes | Yes | Yes |
NINO3.4 | No  | Yes | Yes |
Observations | 177203 | 177203 | 129398 |

$R^2$ | 0.098 | 0.098 | 0.088 |

**Notes:** The table shows results from estimating equation (13) on daily data. Dependent variable is indicated at the top of each column. “Fish” refers to number of fish, while “catch” refers to the pounds of fish. Controls are indicated at the bottom and are year indicators, week indicators, the NINO3.4 index, and NINO3.4$^2$. Standard errors clustered at the vessel level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

of the damages associated with ENSO events. In other words, there are enough adaptation opportunities with an investment horizon of three months or less to almost completely mitigate the impacts of ENSO in this setting. These results are highly significantly different from 0, although in no case can I reject the null hypothesis that they are equal to 1. Because the teleconnection-skill interaction is near zero for the first two specifications, all versions of adaptation potential presented in Section 4.1 will be almost identical.
The tele.\texttimes enso coefficient is also of interest, as it indicates that for teleconnected vessels, an ENSO event is associated with a drop in output of more than 50%. During normal periods, these vessels have higher output, suggesting that they are trading off higher output return for greater output volatility.

The triple differences specification helps alleviate concerns that these results are driven by other confounding factors. Unless the change is correlated with the division into teleconnected and non-teleconnected, then it will be washed out. Since this fishery is not managed by multiple bodies, such concerns with policy will be unlikely to manifest in practice. An assumption underlying the estimates, however, is that the teleconnected and non-teleconnected vessels have common catch trends. Figure 8 shows the average catch time series for teleconnected and non-teleconnected vessels and also offers evidence to support common trends between the two series. One can see that before 1987, the two series tracked each other very well, but that during the El Niño that started in 1987, the two series began to diverge strongly. Recall that forecasts were introduced in 1986 and began to be publically disseminated in 1989.

5.1 Robustness checks

Inference in Table 2 relies on a number of assumptions including common trends in catch between teleconnected and non-teleconnected vessels, the comparability of different days within the season conditional on week of year, and choice of regressors. Here, I investigate some of the more plausible potential failures of these assumptions and provide robustness checks.

First, there is strong seasonality in the fishery, with catch peaking in the mid summer, and little or no fishing in the winter. In the daily specification, I rely on week of year controls to account for these changes. Alternatively, I could have put in finer controls for day of year or some other seasonal control scheme. Such additions do not change inference. In the other direction, I can remove seasonality entirely by estimating at the annual level, as reported in Table 3. Here, all values are aggregated to the season level, so the coefficients should be roughly the same as
in Table 2. On a qualitative level, this is true. Skillful forecasts improve catch, and total adaptation is high. The annual coefficients are quite a bit larger than their daily counterparts, perhaps reflecting the greater degree of near-multicollinierity present in the annual estimates.

Table 3: Total Adaptation: Season

<table>
<thead>
<tr>
<th></th>
<th>log(fish)</th>
<th>log(fish)</th>
<th>log(catch)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teleconnection</td>
<td>0.84***</td>
<td>0.80***</td>
<td>0.54*</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.23)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Skill</td>
<td>0.018</td>
<td>-0.022</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>ENSO event</td>
<td>-0.15</td>
<td>-0.12</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Tele. × skill</td>
<td>-1.90***</td>
<td>-1.73***</td>
<td>-1.54**</td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td>(0.52)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Tele. × ENSO</td>
<td>-1.43***</td>
<td>-1.37***</td>
<td>-1.14***</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(0.35)</td>
<td>(0.43)</td>
</tr>
<tr>
<td>Skill × ENSO</td>
<td>-0.23</td>
<td>-0.18</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.21)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Tele. × skill × ENSO</td>
<td>2.44***</td>
<td>2.42***</td>
<td>2.14**</td>
</tr>
<tr>
<td></td>
<td>(0.71)</td>
<td>(0.71)</td>
<td>(0.87)</td>
</tr>
<tr>
<td>Adaptation</td>
<td>1.70***</td>
<td>1.77***</td>
<td>1.88***</td>
</tr>
<tr>
<td></td>
<td>(0.30)</td>
<td>(0.32)</td>
<td>(0.43)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>NINO3.4</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>7632</td>
<td>7632</td>
<td>6049</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.211</td>
<td>0.213</td>
<td>0.185</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating equation (13) on annual data. Dependent variable is indicated at the top of each column. “Fish” refers to number of fish, while “catch” refers to the pounds of fish. Controls are indicated at the bottom and are year indicators, week indicators, the NINO3.4 index, and NINO3.4$^2$. Standard errors clustered at the vessel level. Significance indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

One potential concern with the estimation strategy presented above is that harvesters could choose to fish in teleconnected areas during normal periods and non-teleconnected areas during ENSO events. Figure 9 compares teleconnection
status during normal and ENSO periods. The figure indicates that there are not systematic differences in teleconnection values between these two periods. It could still be the case that the overall distribution of teleconnection is stable but that the best or worst vessels are differentially sorting between teleconnection zones. First, this is likely not an issue in practice because vessels travel to the same fishing ground repeatedly, so there are many reasons aside from teleconnection to be choosing fishing location. Second, if I regress teleconnection status on a variant of Equation (13) that removes teleconnection and its interactions from the right-hand side, I see that, if anything, vessels are choosing to fish more in teleconnected areas during ENSO events. The results of Table 4 also support this claim, since it shows that there are no systematic movements in the fishery during ENSO events as forecast skill improves. Relatedly, covariate balance can be assessed by looking at the teleconnection term in each regression. One can see that teleconnected vessels are more likely to fish in the western portion of the fishery, are closer to optimal SST gradient, have higher average catch, and take shorter trips. Other covariates appear to be similar.

Finally, I investigated alternative definitions of teleconnection, skill, and ENSO, with results available upon request. For teleconnection, I tested robustness to the Hsiang et al. style monthly aggregation measure and significance masking of the correlation. Both are similar to the baseline estimates given above. For skill, I calculated an alternative measure using 3-month mean squared error rather than the monthly squared error used in the baseline. This change has no effect. I also calculated skill assuming a constant naïve forecast, with little change to results. Finally, I varied the ENSO event measure by including the first lag of the absolute value of the NINO3.4 index rather than an indicator for ENSO events. The results are qualitatively the same, although interpretation of the triple interaction changes due to variability in strength of ENSO events over time.
### Table 4: Mechanisms: Daily location

<table>
<thead>
<tr>
<th></th>
<th>latitude</th>
<th>longitude</th>
<th>log(∆ SST)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teleconnection</td>
<td>-0.17</td>
<td>29.2***</td>
<td>0.36***</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(1.67)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Skill</td>
<td>-0.10</td>
<td>-1.89*</td>
<td>0.0043</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.99)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>ENSO event</td>
<td>-0.036</td>
<td>-1.65***</td>
<td>-0.042**</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.46)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Tele. × skill</td>
<td>5.39***</td>
<td>6.19*</td>
<td>0.30***</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(3.29)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Tele. × ENSO</td>
<td>-0.64</td>
<td>-4.89***</td>
<td>0.26***</td>
</tr>
<tr>
<td></td>
<td>(0.48)</td>
<td>(1.69)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Skill × ENSO</td>
<td>0.12</td>
<td>2.74***</td>
<td>0.15***</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.96)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Tele. × skill × ENSO</td>
<td>-1.42</td>
<td>0.14</td>
<td>-1.07***</td>
</tr>
<tr>
<td></td>
<td>(0.93)</td>
<td>(3.12)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Week FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>NINO3.4</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>185942</td>
<td>185942</td>
<td>132626</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.482</td>
<td>0.540</td>
<td>0.204</td>
</tr>
</tbody>
</table>

*Notes:* The table shows results from estimating equation (13) on daily data. The dependent variable is indicated at the top of each column. Latitude and longitude are measured in degrees, and log(∆ SST) is the log of the difference between observed SST gradient and optimal. Controls are indicated at the bottom and are year indicators, week indicators, the NINO3.4 index, and NINO3.4$^2$. Standard errors clustered at the vessel level. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

### 6 Mechanisms

Table 4 investigates one of the potentially most important daily adaptation mechanisms—location choice. The first two columns use the same regression outlined in Section 4 to investigate changes in latitude and longitude. From Figure 5, one might expect no effect on latitude but some effect on longitude, since teleconnection status changes most from east to west rather than north to south. Alternatively, moving northward is a natural adaptation strategy if waters are warming overall. Instead,
one can see that there is not a systematic change in these spatial measures as forecasts improve (as indicated by the triple interaction terms in columns 1 and 2).

This result is in fact reassuring that gross violations of identification are not occurring, as discussed further below. For instance, if teleconnection status was changing as forecasts improved—a source of potentially pernicious sorting—one would expect that the triple interaction term in column 2 would be of opposite sign from the coefficient on teleconnection. Instead, the term is weakly of the same sign.

In contrast, column 3 shows that vessels are improving outcomes through a more targeted spatial adaptation. The dependent variable is now the log of the difference between the SST gradient that the vessel is observed to be fishing on and the optimal gradient as discussed in Section 3.3. One can see that as the forecast improves, vessels are much more likely to be closer to this optimal value. Moreover, ENSO events before forecasts are introduced push vessels away from optimum, supporting the search model interpretation of this setting.

Trip-level decisions are plausibly even more important than daily location decisions in terms of adaptation, because alteration of trip timing or length can be used to avoid ENSO events entirely. Figure 6 and Table 5 investigate these choices in three ways: through the decision to start a trip, the number of trips taken per year, and the length of trips.

Figure 6 depicts changes in trip start probabilities when forecast skill is equal to 1. The average trip starting probability for a vessel on a given day during the fishing season is 0.1, so the figure indicates that trips are much more likely to begin during ENSO events once forecasts have high skill. In contrast, coefficients from the same model, not shown, indicate that periods during which forecasts have low skill have lower than average trip start probabilities during ENSO events.

Similarly, Table 5 shows that teleconnected vessels take more trips during the year once forecasts are of high skill, and that these trips last longer. These results suggest that the forecasts allow vessels to plan longer trips in advance.
7 Conclusion

Environmental impacts from a variety of sources are currently large and, for many important cases, are not being solved by collective action. Thus, individual and firm adaptation will likely be one of the largest forces mitigating these impacts. Adaptation does not occur in a vacuum, however, since individuals will need to know about their own risks to make informed choices over potential adaptive responses. The importance of this issue makes it crucial to assess the role of information in adaptation and allows one to use informational changes to estimate the effect of this adaptation.

In the setting of one large driver of global climate—ENSO—and highly mobile firms in the form of North Pacific albacore harvesters, I assess this issue using an estimating equation informed by a structural model of adaptation. Detailed, daily panel data and a unique set of real-time historical ENSO forecasts allow for estimation of the role of information in climate adaptation. I find that moving from...
Table 5: Mechanisms: Trip choice

<table>
<thead>
<tr>
<th></th>
<th>Number of trips per year</th>
<th>Trip length (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teleconnection</td>
<td>0.43</td>
<td>-13.0***</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(4.24)</td>
</tr>
<tr>
<td>Skill</td>
<td>0.47</td>
<td>11.9***</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(3.85)</td>
</tr>
<tr>
<td>ENSO event</td>
<td>-0.36**</td>
<td>7.11***</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(2.04)</td>
</tr>
<tr>
<td>Tele. × skill</td>
<td>-1.01</td>
<td>-33.5***</td>
</tr>
<tr>
<td></td>
<td>(0.86)</td>
<td>(11.5)</td>
</tr>
<tr>
<td>Tele. × ENSO</td>
<td>-1.05**</td>
<td>-16.0***</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(5.17)</td>
</tr>
<tr>
<td>Skill × ENSO</td>
<td>0.056</td>
<td>-10.8***</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
<td>(4.12)</td>
</tr>
<tr>
<td>Tele. × skill × ENSO</td>
<td>2.93**</td>
<td>47.1***</td>
</tr>
<tr>
<td></td>
<td>(1.22)</td>
<td>(12.2)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>NINO3.4</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>7587</td>
<td>7575</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.208</td>
<td>0.157</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating equation (13) on annual data. The dependent variable is indicated at the top of each column. Latitude and longitude are measured in degrees, and log($\Delta$SST) is the log of the difference between observed SST gradient and optimal. Controls are indicated at the bottom and are year indicators, week indicators, the NINO3.4 index, and NINO3.4$^2$. Standard errors clustered at the vessel level. Significance indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A 3-month ahead ENSO forecast with no skill to a forecast with perfect skill raises catch rates by climate impacted vessels during adverse climate events by more than 50%. This estimate implies that the potential adaptation in the fishery is at least 88% for the average vessel.

Secondarily, I examine some mechanisms by which the vessels utilize the forecasts to achieve this catch improvement. In particular, the choice of fishing location and timing of trips are both compared between ENSO periods and non-ENSO periods as forecasts improve. Regression results indicate that climate impacted vessels use the forecasts to move eastward in response improvements in forecasts and that these vessels start their season closer to winter.
These estimates inform the potential effectiveness of information as a climate adaptation policy. According to the baseline results, forecast provision has been extremely helpful in mitigating the damage from ENSO in the setting of albacore fishing. It is important to note that rather than indicating that adaptation is “policy-free” in the sense that it will occur without intervention, the results here point to the direct value of policy-driven information provision.

These results are encouraging for the prospects of other highly mobile firms or individuals with many in-place adaptation options. Caution should be exercised, however, in over-interpreting the results as indicating that these settings will be robust to long-term climate change. Indeed, as Hornbeck and Keskin (2014) illustrates, adaptation can be perverse in the sense that a relaxation of one constraint can allow individuals or firms to place themselves in an even more precarious long-run position—a return to the Malthusian edge. In the empirical setting presented here, it might be the case that higher catch during ENSO events will lead to reductions in biomass, thus harming the fishery in the long-run.

Positively, the method presented here is not unique of the setting. Although data requirements are high, the novel collection of ENSO forecasts assembled for this project and the general estimation strategy should allow for investigation of adaptation to ENSO processes in a number of different settings. Another potentially fruitful avenue would be to explore adaptation to forecasts of different lead times, up to and include years, to assess historical adaptation across many temporal levels.
References


Graff Zivin, J., M. Neidell, and W. Schlenker (2011). Water quality violations and


A  ENSO forecast data

Gathering actual contemporary forecast values (what I call “real time forecasts”) was of great importance for this project, because good knowledge of the information sets available to harvesters is crucial for identification. Unfortunately, no centralized database of real time ENSO forecasts from their initiation to the present exists. Thus, I gathered real time forecasts from the Climate Diagnostics Bulletin (CDB) and the IRI Niño 3.4 summary. The CDB started releasing forecasts in June 1989 and began incorporating the IRI summaries in April 2003. By the year 2000, the number of forecasts incorporated into the Bulletin had grown from 1 to 8.

To gather the CDB data, I digitized paper records from 1989 to 1999 by scanning each forecast from the Bulletin and then recording the data using Graphclick. For Bulletins from 1999 to 2002, I used the online archive of CDBs, again digitizing the figures using Graphclick. Where available, I digitized the CDC CCA, LDEO1, LDEO2, LDEO3, LIM, and NCEP forecasts. Other forecasts were either issued as maps or contained idiosyncratic issues that prevented digitization.

For data from 2002 through 2010, I used IRI data helpfully supplied to me by Anthony Barnston.

In all cases, I used the actual ENSO index values reported in subsequent CDB or IRI reports to calculate forecast accuracy. So, for instance, when digitizing the Climate Prediction Center Canonical Correlation forecast at a 3 month lead, I used the actual value reported in the CDB three months later. One could alternatively use a standardized ENSO index across all forecasts. I chose not to do this for numerous reasons. First, all forecasts initially, and many forecasts to the present day, use the NINO3 index rather than the NINO3.4 index. Second, the base climatology used to calculate ENSO indices has changed from the 1980s to the present. Third some forecasting agencies might have used their own idiosyncratic calculations of an index or used alternative SST measures. Using the real-time actual values eliminates these sources of noise. On the other hand, what matters for fishing outcomes is the true climate that realized each time period. Thus, for
estimation, I use the most recently released version of the NINO3.4 index. For an alternative method based on scaling alternative index values and visual averaging of maps, see the IRI ENSO *Quick Look*.

For the timing of forecast release, I have assumed that all Bulletins were released on the 18th of the month. This is not precisely accurate, but prior to 2002, I cannot determine the exact date of release. Examination of the Bulletins after 2002 show that the release date is near the 18th, and almost always between the 14th and 21st of the month.
B Appendix tables and graphs

Figure 7: North Pacific Albacore Fishery Spatial Distribution

Notes: The heat map indicates catch by U.S. albacore harvesters in each 1/4° grid cell in the North Pacific from 1981-2010.

Figure 8: Difference in differences trends

Notes: The graph shows 12 month moving average log catch for teleconnected (blue) and non-teleconnected (green) vessels. The pink periods are El Niño events and the light blue periods are La Niña events. Forecasts were introduced in 1989.
Figure 9: Teleconnection choice

Notes: The histogram shows teleconnection values during normal periods (gray) and ENSO events (black outlines).

Figure 10: ENSO impact by teleconnection

Notes: The figure shows local linear polynomial smoothing of differences in log catch between teleconnected and non-teleconnected vessels over a range of absolute NINO3.4 values. Log catch has been normalized to equal zero for both series at zero NINO3.4.
C Model extensions: Centralized signals versus idiosyncratic beliefs

One can extend the model from Section 2.3 to incorporate multiple signals to distinguish between idiosyncratic learning and improvements based on centralized forecasts. Assume each harvester $i = 1, \ldots, k > 2$, gets i.i.d. signals $s_i \sim N(\bar{\tau}_i, 1)$. Each harvester wants to minimize loss:

$$u(\tau_i) = -(\bar{\tau}_i - \hat{\tau}_i)^2$$

So, $\hat{\tau}_i^* = \bar{\tau}_i$. Without additional signals, optimal forecast is thus $\hat{\tau}_i^* = s_i$

Now, let centralized forecasts exist, denoted $T = (T_1, \ldots, T_k)'$. Assume that $T_i = T_j$ for all $i$ and $j$. What forecast should harvesters use now? Using Stein (1956) and Efron and Morris (1975), we have that if the harvesters are Bayesian updating, the optimal location forecast becomes

$$T_i^* = \theta s_i + (1 - \theta)T_i$$

where $\theta = 1 - \frac{(k-2)}{\sum_{i=1}^{k} (s_i - T_i)^2}$.

In this case,

$$E \left[ \sum_{i=1}^{k} (\bar{\tau}_i - T_i^*)^2 \right] < E \left[ \sum_{i=1}^{k} (\bar{\tau}_i - \hat{\tau}_i^*)^2 \right]$$

This condition implies that after centralized forecasts are released, the RMSE of processes in the fishery will fall to the extent that centralized forecasts dominate individual signals. Assuming unbiasedness of signals, this will manifest in a fall in variance of adaptation processes. I explore this implication in Table 6, which shows the change in variance of trip departure date, experienced SST, latitude, longitude, and log of catch from the period before forecasts were released and the period after forecasts were released. In all cases, the variance of these processes falls.

Learning about the forecasts might also be idiosyncratic and important for
Table 6: Change in Variance Post Forecasts

<table>
<thead>
<tr>
<th>Variable</th>
<th>ΔVariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>departure date</td>
<td>-13.19</td>
</tr>
<tr>
<td>SST</td>
<td>-0.42</td>
</tr>
<tr>
<td>Latitude</td>
<td>-1.43</td>
</tr>
<tr>
<td>Longitude</td>
<td>-11.93</td>
</tr>
<tr>
<td>ln(catch)</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

their take-up, the degree to which they aid adaptation, and the interpretability of Section 5 results as total possible adaptation. Future results will incorporate reported uncertainty in forecasts to further assess the role of learning in forecast adoption and use.
D Proofs

Proposition 2.1: If $E[u_{it}|z_i, \alpha_i] = 0$ for $t = 1, \ldots, T$, and both $\sum_{t=1}^{T} E[z_{it}^t \bar{z}_{it}]$ and $\sum_{t=2}^{T} E[\Delta \bar{z}_i z_i]$ are of rank $K$, then the estimates from Equation (4), $\hat{\beta}^{FE}$, and the estimates from Equation (6), $\hat{\beta}^{LD}$ are consistent for $\beta$ from Equation (1) and are therefore asymptotically equivalent.

Proof. The consistency of $\hat{\beta}^{FE}$ is a standard result. See, for instance, Wooldridge (2010, Ch. 10).

The consistency of $\hat{\beta}^{LD}$ comes from first noting that Equation (6) can be written as a series of sums and differences of the fixed effects equation. Namely, denote $T_j$ the length of the time period over which long differences are constructed, so $T = T_1 + T_2 + \cdots + T_L$. To match the definition of long differences given above, let $T_k = T_j$ for all $k$ and $j$ so $T = L \times T_j$. Then, one can construct the long difference estimating equation by adding and subtracting the appropriate values from the first difference equation

$$T_j^{-1} \left( \sum_{t=t_j}^{t_j+T_j} y_{it} \right) - T_j^{-1} \left( \sum_{t=t_j-T_j}^{t_j} y_{it-1} \right) = \Delta \bar{y}_{it_j}$$

$$= \Delta \bar{z}_{it_j} \beta + \Delta \bar{u}_{it_j} \quad (17)$$

Thus, it suffices to show that $E[u_{it}|z_i, \alpha_i] = 0$ implies $E[\Delta \bar{u}_i|z_i, \alpha_i] = 0$. This is immediate from the linearity of expectation. \qed