Expectations and Adaptation to Environmental Risks

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Abstract

Climate change is expected to have large, negative effects on the global economy. Responses to a changing climate—adaptation—will affect how much damage ultimately occurs. This paper introduces a method for estimating forward-looking adaptation based on differences in responses to forecasts and realizations of weather. The method is applied to estimate adaptation in a fishery using a novel dataset of climate forecasts and detailed, firm-level data. In this setting, most of the effect of climate variation can be controlled through adaptation. Important adaptation mechanisms involve reducing production costs and timing entry into the fishery. (JEL:D22,D84,Q22,Q54)

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1 Introduction

Climate change is predicted to cause substantial damage to the global economy. The ultimate amount of damage will depend on both public policy to reduce emissions of greenhouse gases and on actions taken by individuals and society to adapt to a changing climate. Despite the role that adaptation plays in determining climate change outcomes, little is known about the total adaptation potential of climate-exposed industries or the economy. Much of what is known comes from analysis of a limited set of adaptive behaviors and from \textit{ex post} adaptation to experienced weather rather than \textit{ex ante} adjustments made in expectation of climate change. Forward-looking or \textit{ex ante} adaptation could be especially important in the context of climate change. Not only does it avoid damages before they occur, but as expectations about the climate evolve, such behavior will be an increasingly large part of the response to climate change.

Estimating adaptation is challenging. Many individual mechanisms—choosing different inputs, altering consumption patterns, switching technology—might help reduce damage from a changing environment. An extensive literature has shown that individuals and firms do adapt to environmental changes along a number of dimensions.\footnote{For some recent examples, see Deschênes and Greenstone (2011), Graff Zivin and Neidell (2012), Graff Zivin et al. (2014), Barreca et al. (2016), Deschênes et al. (2017), and Taraz (2017).} For policy, we would like to know the damage that results from changes in the environment after \textit{all} adaptation mechanisms have been incorporated as well as the aggregate cost of these adaptations. Identification of the overall benefit of adaptation either requires \textit{a priori} knowledge of each adaptation mechanism available to agents and suitable exogenous variation for each one, or it involves finding a way to identify the overall effect of adaptation without reference to the underlying mechanisms. Following the work of Dell et al. (2009), a recent literature has used average weather to estimate environmental effects that incorporate adaptation and used high frequency variation in weather to measure effects holding adaptation fixed. If low frequency weather variation captures effects including adaptive responses while high frequency variation captures effects without adaptation, then comparison of these estimates provides a measure of the overall effect of adaptation.\footnote{These papers generally fall into one of two groups: those using short-run variation in the weather to get without-adaptation estimates and cross-sectional average weather to get with-adaptation estimates, as in Dell et al. (2009, 2012), Hsiang and Narita (2012), Butler and Huybers (2013), Schlenker et al. (2013), Moore and Lobell (2014), and an approach that compares short-run variation to sub-sample average weather following Burke and Emerick (2016). For a review, see Dell et al. (2014). One other, related method estimates damage from climate or environment over different subsamples of the data over time and infers adaptation from changes in this relationship, as in}
on individual adaptation mechanisms, these studies have generally found that total adaptation has little to no effect on output losses from weather.\footnote{Two exceptions are Dell et al. (2009) which finds evidence for substantial adaptation in the relationship between gross domestic product and temperature when comparing rich countries to poor countries. Over the last 50 years, however, Dell et al. (2012) shows that temperature effects on GDP have not weakened within income groups, a point reinforced by Burke et al. (2015). Barreca et al. (2016) find that the effect of temperature on mortality fell substantially over the 20th century and attribute much of this decline to air conditioning.}

In this paper, I introduce a new method for estimating the marginal benefit of adaptation and the effect of weather conditional on that adaptation. The marginal benefit of all \textit{ex ante} adaptation engaged in by firms is identified from changes in forecasts of upcoming weather.\footnote{A small but growing literature in environmental economics is using forecasts to study forward-looking behavior. Neidell (2009) looks at the effect of pollution forecasts and public announcements on consumer behavior, Rosenzweig and Udry (2014) use monsoon forecasts to study optimal weather insurance for farmers, and Severen et al. (2016) ask whether farm land values have incorporated information from long-run climate forecasts. A recent theoretical treatment is in Lemoine (2017).} Conditional on forecasts, realizations of weather identify a combination of \textit{ex post} adaptation and the direct effect of weather holding adaptation fixed. If all adaptation is \textit{ex ante}, then the method exactly identifies the marginal benefit of all adaptation and the direct effect. This method contrasts with previous studies of adaptation both in terms of the object of interest, the assumptions necessary for identification, and data requirements.

Intuitively, identification comes from the exploiting the difference between news about future fluctuations versus the realization of those fluctuations. News, measured by conditioning forecasts on realizations of weather, causes a firm to alter inputs in preparation for the upcoming fluctuation. These changes in inputs are adaptation. \textbf{The effect on revenue of these changes provides a measure of the benefit of adaptation. Therefore, the marginal benefit of all \textit{ex ante} adaptation can be estimated by looking at how firm revenue is affected by news about an upcoming environmental change. Under an additional assumption that the firm sets all inputs before the state realizes, forward-looking adaptation is equal to total adaptation. In this case, the method also identifies the direct effect of weather (holding adaptation constant) via the effect on revenue of weather realizations conditional on forecasts.\footnote{If firms can respond to weather \textit{ex post}, then the method bounds total adaptation from below and bounds the direct effect from above.} Estimates of the benefit of adaptation and direct effect provide a complete picture of the effect of weather on a firm.}

The method shares the benefit of the work following Dell et al. (2009) that the re-
searcher need not know the full suite of adaptation mechanisms available to an agent. This is because the forecast captures the aggregate effect that all forward-looking input changes have on firm revenue. The method also has some unique benefits. First, the method identifies the benefit of forward-looking adaptation. Adaptation that occurs in advance of a change in the environment could be particularly important in many environmental contexts, including climate change, because disaster can result from a failure to avoid the bad state. Second, by allowing the researcher to use firm revenue as the dependent variable, data requirements are reduced relative to envelope theorem-based methods that require profit, land prices, or similar measures (Deschênes and Greenstone, 2012, Hsiang, 2016). Third, the method allows for straightforward generalization to cases with discrete adaptation mechanisms. By estimating reduced-form relationships that capture the benefits of all adaptation mechanisms, the estimates average over both continuous and discrete inputs. Fourth, by using a time varying measure of expectations, this strategy allows for empirical methods that alleviate omitted variable bias concerns. For instance, fixed characteristics of individuals or locations can be controlled for through typical panel data approaches.

Applying the method, I estimate the degree of forward-looking adaptation to El Niño/Southern Oscillation (ENSO) by albacore tuna harvesters in the North Pacific. The empirical setting is particularly suitable for using forecasts to estimate adaptation. ENSO is a major source of global climate variation stemming from periodic but stochastic warming and cooling of the equatorial Pacific Ocean. ENSO was believed to be unforecastable as recently as the mid-1980s. Within the decade, however, breakthroughs in modeling, computing, and data collection allowed climatologists to create accurate forecasts of ENSO multiple months in advance. Concurrent with these developments, the National Oceanic and Atmospheric Administration (NOAA) began a program to disseminate these forecasts to ENSO-exposed fisheries. The albacore fishery, historically a setting where output and profit declined substantially during ENSO events, was one such fishery. Because the fishery is spatially distant from the area where ENSO forms, these forecasts and attendant NOAA reports on ocean conditions were plausibly the main source of ENSO information available to albacore harvesters over the sample period.

Estimates show that the information in the forecasts is important to the fishery.

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6Some researchers have questioned whether individuals will perform substantial *ex ante* adaptation in real-world settings (Mendelsohn, 2000). The method presented here allows for quantification of the degree of forward-looking adaptation, and the empirical results show that such adaptation is practically important.
Forecasts have a ten times larger effect on output than do the realizations of ENSO. Interpreting this through the lens of the model, the estimates suggest that the benefit of forward-looking adaptation is large relative to the direct effect of ENSO holding adaptation fixed. The results also show that if adaptation were ignored (by excluding forecasts from the regression), estimates of the effect of ENSO on the fishery would be biased in two ways. First, the direct effect of ENSO would be overstated because positive correlation between forecasts and realizations would cause some of the adaptation effect to be attributed to the direct effect. Overstatement of the direct damage from an environmental process when adaptation is ignored is a central concern when setting appropriate mitigation policy Mendelsohn et al. (1994). Second, the total effect of ENSO would be understated because realizations of ENSO do not capture the full benefit of forward-looking adaptation that is identified by variation in expectations. If adaptation is costly, this understatement would lead to sub-optimally weak policy responses.

Exploiting the richness of the spatially explicit, high-frequency, firm-level data, secondary results examine mechanisms by which the vessels use the forecasts to adapt. Overall, vessels respond to the forecasts by reducing their fishing effort and expenditures during adverse periods. On the intensive margin, in anticipation of ENSO, harvesters fish fewer hours per days, move less during fishing trips, and employ fewer fishing lines. Similarly, within a month that the vessel chooses to go fishing, vessels fish for fewer days and take slightly fewer trips per month if they anticipate that climate conditions will be bad. Across months, harvesters avoid participating in the fishery—either by declining to enter the albacore fishery or by exiting more quickly if they are currently fishing albacore—if they expect conditions to be poor.

In contrast, the effect of realized ENSO conditional on the forecasts causes little or no change in any of these behaviors. Overall, the mechanism analysis supports the primary result. Revenue falls when the forecast of ENSO is high, but the behaviors engaged in by the firm are generally cost-saving, so the firms insulate themselves from negative profit shocks. Looking explicitly at measures of revenue net of movement costs, I find that net revenue is less effected than revenue by forecasts of ENSO. This is in line with the predictions of the model.

Finally, the model can be extended to study firm risk tolerance and learning. I adopt the reduced form of the model from Rosenzweig and Udry (2014) to determine whether the firms in this setting are risk averse. Intuitively, a risk-averse firm should care both about the level of the forecast and its \textit{ex ante} uncertainty. In this setting, firms do appear to be risk averse. The past accuracy of ENSO forecasts (as measured
by recent, historical mean squared forecast error) and a narrowing of the dispersion of
the members of the forecast ensemble both cause higher levels of adaptation. Second,
firms with more ENSO experience are better able to adapt than novice firms. To-
gether with the headline estimates, these results highlight both the opportunity and
limitations of using information as a public policy response to environmental changes.

ENSO is an important, global driver of climate variation that, in addition to
fisheries, also affects health, civil conflict, agricultural productivity, and worldwide
commodity markets among other outcomes (Kovats et al., 2003, Hsiang et al., 2011,
Solow et al., 1998, Brunner, 2002). The results from this paper show that economic
agents can manage their risk from this climate process by making ex ante adaptation
decisions. In the context of broader, global climate change, if vessels are able to
adapt to changing ocean temperatures due to climate change in a way that is similar
to how they have adapted to ENSO, then the results suggest that realized climate
change damages might be greatly reduced.7 Application of the method developed in
the paper to additional settings can shed light on adaptation more broadly. The novel
dataset of ENSO forecasts created for the project can be used to assess adaptation to
this climate process across the globe, and use of routine weather forecasts can help
understand the scope for weather adaptation more generally.

Outside the context of environmental adaptation, the paper illustrates the contribu-
tion that analysis of forecasts of environmental processes can make to understand-
ing long-standing problems in firm and consumer theory. For instance, the theory
of adaptation shares a formal similarity with theories of firm flexibility introduced
by Stigler (1939). Such theories are generally difficult to test due to a lack of data
on expectations. Using environmental forecasts will allow for investigation of firm
trade-offs in stochastic settings. Forecasts of environmental processes are well suited
to study these issues not only because they are routinely used by firms and are easily
observable by the researcher, but also because the variation in the underlying en-
vironmental processes is often economically exogenous.8 This feature contrasts with
other settings, like finance, where forecasts have the potential to endogenously change
the state, complicating empirical analyses. In the future, growing bodies of data and

7Adaptation dynamics could play an important role when extrapolating from the medium-term
variation considered in this paper to the longer-term changes caused by global climate change.
Investigation of the timing and durability of adaptation will help shed light on this issue. Adaptation
costs also need to be incorporated into a full welfare accounting of adaptation’s ability to reduce
climate change damages (Deschênes et al., 2017). The results from this paper can be used to bound
the costs of adaptation from above.

8Although, as this paper shows, expectations must be accounted for to arrive at econometric
exogeneity.
falling costs of data analysis imply that more firms will be making expectation-driven investments, increasing the need and opportunity to study forward-looking behavior.

The rest of the paper proceeds as follows: Section 2 formalizes the role of expectations in adaptation, provides conditions under which public forecasts can act as good proxies for agent expectations, and shows that a regression framework can identify both climate adaptation and direct weather effects. Section 3 gives background on the empirical setting and discusses the data. Section 4 lays out the specific empirical analysis that will be performed on the data, and Section 5 reports the results of estimating that model as well as robustness checks and tests of assumptions. Section 6 investigates adaptation mechanisms over multiple time horizons. Section 7 examines heterogeneity in the adaptation response and draws out additional implications of forecast-driven adaptation. Finally, Section 8 concludes.

2 Identifying adaptation

2.1 Expectations identify ex ante adaptation

Economic adaptation is commonly defined as the actions taken by an individual or group of individuals to help reduce the negative effects of a potential change in the environment or to capitalize on gains from such a change.9 Formalizing this notion of adaptation helps clarify how to estimate both adaptation and the total impact from environmental shocks. In particular, a formal definition of adaptation will generalize from the single adaptation strategies or mechanisms that much of the economics literature has focused on—staying indoors on hot or polluted days (Neidell, 2009, Graff Zivin and Neidell, 2009), changing the mix of crops or the use of agricultural inputs (Rosenzweig and Udry, 2014, Hornbeck and Keskin, 2014), air conditioning (Barreca et al., 2016), or migrating (Deschênes and Moretti, 2009)—to the overall effect of adaptation on an individual’s welfare.

For policy, one would like to know the overall benefit of adaptation incorporating each of the underlying adaptation mechanisms. Such a value is necessary for decomposing environmental impacts into the effect that an agent chooses to control—the adaptation effect—and the residual portion that the agent does not or cannot adapt away—the direct effect. In this study, I use changes in expectations held by agents to estimate the value of forward looking adaptation. This is the benefit to the agent of all behavioral responses that occur in advance of a change in the future state of the

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9For examples of such a definition, see the Environmental Protection Agency’s climate change website (19january2017snapshot.epa.gov/climatechange/adapting-climate-change_.html) or IPCC (2014). This study will focus on adaptation by a single economic agent.
environment. Expectations drive such changes, as a consideration of the link between the adaptation mechanisms listed above makes clear. In making investment decisions or decisions like migration that involve high fixed costs, it is natural to characterize behavior as stemming from an expectation that conditions will warrant the investment in the future. For behaviors that take time to set up or realize, expectations also play an important role.

Formalizing the effect of beliefs on forward-looking adaptation in a simple model provides the basis for econometric identification. Consider a firm producing a univariate output at time $t$ which is a function of random weather as well as inputs that are chosen by the firm. Assume that the firm’s choices only affect profit this period.\footnote{In my empirical setting, I will analyze outcomes at the monthly level, and harvesters rarely take trips lasting for more than a month. For evidence on other fisheries, see Costello et al. (2001). For an extension to durable investments, see Lemoine (2017).} To emphasize the uncertain effect of weather on the production process, assume that the firm must choose each input, $x_{jt}$, before the weather in period $t$ is realized.\footnote{For the more general model considering inputs chosen after weather has realized, see Section A. At the end of this section, I discuss which identification results hold for the entirely \textit{ex ante} model presented here versus the more general model. For an extension to the case with finite adjustment costs, see Downey et al. (2019).} At the beginning of each period, the firm’s problem is to maximize expected profit

$$\max_x E_{t-1}[\pi_t] = p_t f(x_t) E_{t-1}[g(Z_t)] - c_t^t x_t \quad (1)$$

Output price are denoted by by $p$, $c$ is the $J$-dimensional vector of input prices, $x$ is the $J$-dimensional vector of inputs, and $Z$ is a stochastic weather variable with at least one finite moment.\footnote{For an extension of the model to production functions of the form $f(x, z)$, see Section A. Multiplicative separability is assumed here for ease of presentation. Also, the model is presented with a single weather variable, $Z$, but nothing prevents the inclusion of a vector of weather variables. In that case, the vectors of derivatives given below would be replaced by Jacobian matrices.} Further assume that $f(x)$ is twice continuously differentiable and concave.\footnote{See Section A for the extension to discontinuous inputs. Identification remains unchanged, but the welfare conclusions discussed below will change. The function $g$ need not be differentiable because the firm is not directly choosing $Z$.} As is standard, a subscript on an expectation operator denotes the information set on which the expectation is conditioned, so $E_{t-1}[g(Z_t)]$ is the expected weather this period conditional on information about the weather in all time periods up to and including the most recent period.

Denote realized revenue by $y_t = p f(x_t) g(z_t)$ and \textit{ex ante} revenue as the expectation of this term with respect to information at $t - 1$. Prices are assumed to be constant.
consider prices that are a function of the climate. The estimator of total adaptation used here will be unaffected by allowing for climate-driven output price changes under additional assumptions on the elasticity of demand for the firm’s output that would rule out extra risk taking during adverse events (Allen et al., 2016).

An optimizing firm chooses inputs to maximize the value of Equation (1). Aside from the weather variable, the problem is a standard one, as indicated by the representative first order condition.

\[
p_t \mathbb{E}_{t-1}[g(Z_{it})] \frac{\partial f(x_{it})}{\partial x_{jit}} = c_{jt}. \tag{2}
\]

Adaptation, as per the above definition, is the response of agents to anticipated changes in environmental conditions. In the context of the model, the agent chooses inputs, and environmental conditions are determined by the distribution of weather.

The first order conditions make three things clear. First, adaptation is the set of changes in all inputs in response to a change in weather. Optimized inputs implicitly defined by Equation (2) can be denoted \( x^*_j(p, c, \mathbb{E}_{t-1}[g(Z_t)]) \) for all \( j \) and \( t \), so the formal definition of adaptation is

\[
A_t = \left( \frac{\partial x^*_1(p, c, \mathbb{E}_{t-1}[g(Z_t)])}{\partial \mathbb{E}_{t-1}[g(Z_t)]}, \ldots, \frac{\partial x^*_J(p, c, \mathbb{E}_{t-1}[g(Z_t)])}{\partial \mathbb{E}_{t-1}[g(Z_t)]} \right) = \frac{\partial x^*_t}{\partial \mathbb{E}_{t-1}[g(Z_t)]} \tag{3}
\]

Second, in the continuous case, optimal adaptation is determined by an equivalence between the marginal cost of adapting and the marginal benefit of adapting. The return on each adaptation mechanism is a function of the marginal productivity of each input as well as the expectation of the firm about the future state. This equivalence suggests that, in principle, estimates of adaptation could come from exogenous changes in any of these variables. To estimate overall adaptation benefits or costs, however, one would need to have prices for all adaptation mechanisms or shocks to all marginal products. Aside from the high data hurdle, such a procedure requires the researcher to know the full set of available adaptation mechanisms \textit{a priori}.

Using expectations, in contrast, allows the researcher to be agnostic about the set of available mechanisms because expectations will capture the reduced form effect of all forward-looking adaptation decisions. In this model, the marginal benefit of adaptation is the adaptation vector multiplied by the revenue value of those changes.

\footnote{In the empirical setting, the assumption of prices being uncorrelated with weather is testable and appears to hold. See Section C.}
denoted

\[ B(A_t) = \frac{\partial E_{t-1}[y^*_t]}{\partial x^*_t} \cdot \frac{\partial x^*_t}{\partial E_{t-1}[g(Z_t)]} \] (4)

where arguments of the maximized output and choice variables have been suppressed for brevity. Estimating this value is one of the primary goals of the paper. Understanding the benefit of adaptation is important for generating accurate estimates of the direct effect of weather, as will be described below. The benefit of adaptation is also useful for bounding adaptation costs. Adaptation costs need to be taken into account when assessing the benefits of addressing environmental externalities, because addressing the externality saves on such costs (Deschênes et al., 2017).

In the continuous model presented here, adaptation is welfare neutral on the margin.\textsuperscript{15} For discrete adaptation like changes in land use or technology choice, Guo and Costello (2013) shows that the benefits of small increases in adaptation can exceed the costs. For those cases, the derivatives in Equation (3) can be replaced by differences. Adaptation is then the change in inputs, broadly defined, in response to changes in the environment and the benefit of adaptation bounds the costs of adaptation from above.

The direct effect of weather is the residual effect conditional on adaptation. In the context of the model, the direct effect is

\[ \frac{\partial E_{t-1}[y^*_t]}{\partial E_{t-1}[g(Z_t)]} = pf(x^*_t) \] (5)

Under the assumption that all adaptations are forward looking, the direct effect of weather on revenue is equal to the direct effect of weather on profit. This assumption rules out amelioration behavior which happens after the state realizes (Graff Zivin and Neidell, 2013). In a more general model, discussed in Section A, that incorporates choices made after the state realizes, it can be seen that both expectations and realizations of weather enter a more general adaptation term and that the method outlined here provides an upper bound on the direct effect.

The theory presented so far shows that if a researcher observes the beliefs agents hold about the weather and has access to \textit{ex ante} data, then both the value of adaptation and the direct effect of weather can be estimated. Here, I show that these

\textsuperscript{15}In papers that use the envelope theorem to estimate climate effects, the equivalence between marginal benefits and marginal costs of adaptation at optimum is exploited to recover direct effect estimates (Mendelsohn et al., 1994, Deschênes and Greenstone, 2007, Hsiang, 2016).
values can also be identified using *ex post* data.\textsuperscript{16} In the next section, I argue that weather forecasts can provide a good proxy for agent beliefs.

Intuitively, identification is driven by the assumption that, conditional on expectations, realized weather does not influence the input decisions made by firms at the beginning of each period. Under this assumption, holding expectations fixed also holds inputs (adaptation) fixed. Varying the realization of weather in this case traces out the direct effect of weather on revenue. Changes in expectations holding realizations fixed have a complementary effect. Only forward-looking inputs are varied, identifying the output effect of adaptation.

Formally, inputs are a function of expected weather (versus realized weather), so

$$
E_{t-1} [f(x^*(p, c, E_{t-1} [g(Z_t)]))] = f(x^*(p, c, E_{t-1} [g(Z_t)]))
$$

Thus, changes in realized weather identify the direct effect because

$$
\frac{\partial y_t}{\partial g(z_t)} = pf(x^*) = \frac{\partial E_{t-1} [y_t]}{\partial E_{t-1} [g(Z_t)]}
$$

For identification of the adaptation effect, note first that with respect to the information at time $t-1$, $\frac{\partial x^*(p, c, E_{t-1} [g(Z_t)])}{\partial E_{t-1} [g(Z_t)]}$ is known, so $E_{t-1} [\partial x^*/\partial E_{t-1} [g(Z_t)]] = \partial x^*/\partial E_{t-1} [g(Z_t)]$.

Showing that $E_{t-1} [\partial y_t/\partial E_{t-1} [g(Z_t)]] = \partial E_{t-1} [y_t]/\partial E_{t-1} [g(Z_t)]$ requires an interchange of integration and differentiation. The assumption of monotonicity of output with respect to $x$ allows for the application of the dominated convergence theorem, so this interchange is valid. Together, then, these two results show that the expectation of the derivative of *ex post* output with respect to expected weather recovers the partial derivative of *ex ante* output with respect to expected weather.

### 2.2 Using public forecasts to measure beliefs

Given the identification argument presented above, the ideal estimating equation to measure adaptation and direct effects from weather would be

$$
y_t = \alpha_0 + \alpha_1 g(z_t) + \alpha_2 E_{t-1} [g(Z_t)] + \nu_t,
$$

\textsuperscript{16}Parametric identification results with a known functional form for $g$ are shown here. For the more general case with non-separable inputs and non-parametric identification, see Section A.1.
where $\mathbb{E}_t^{p-1}[g(Z_t)]$ is the private expectation that the agent holds about the weather next period and $g(z_t)$ are realizations of weather.\(^{17}\)

Observing these private expectations is usually not possible in practice, and finding good proxies for agent beliefs is challenging in general. Researchers studying weather effects, however, are well positioned to employ a method with many good theoretical properties—using professional forecasts of the relevant weather process as the measure of agent beliefs. Modern weather forecasts are formal statements of the expectations of the forecaster about future conditions, and many individuals and firms rely on these forecasts to make weather-contingent plans. Therefore the forecasts have the potential to capture some or all of the information contained in the expectations of private agents while being observable and therefore amenable to estimation.

Professional forecasts will provide a good measure of agent beliefs under the assumptions that the forecasts are public, that agents are maximizing expected profit, and to the degree to which the forecasts capture the full information available to agents. Under these conditions, it can be shown that forecasts are good proxies for agent expectations.

To see this, denote the public forecast as $\widehat{g}(z)$, and consider the public forecast as a proxy for the private expectation (Wooldridge, 2010, ch.4). The first condition for a good proxy is that it is redundant with the variable being proxied for. In this case, redundant means that if the true expectations of the agent were observed, then the public forecast would not be helpful in explaining revenue. Formally, that $\mathbb{E}[y|g(z), \mathbb{E}^{p}[g(Z)], \widehat{g}(z)] = \mathbb{E}[y|g(z), \mathbb{E}^{p}[g(Z)]]$. Optimization ensures that this condition will be satisfied. Private beliefs should always be either equal to or sufficient for the public forecast (if not, then the agent is losing profit by ignoring information), so conditioning on public forecasts will not add any information relative to conditioning on private forecasts.

The second condition for a forecast to be a good proxy is, informally, that it removes the endogeneity of realized weather that occurs if agent expectations are not taken into account in Equation (6). Writing public forecast as a linear projection of private beliefs

$$
\mathbb{E}_t^{p-1}[g(Z_t)] = \theta_0 + \theta_1 g(z_t) + \xi_t
$$

\(^{17}\)If the agent is forming or using reasonable forecasts of weather to determine their expectations, these two terms will be positively correlated. In practice researchers might have difficulty separately identifying both the effect of expectations and realizations. The empirical setting of this paper involves forecasts that are good but not perfect (see Figure A5), leaving identifying variation in both variables.
this condition can be formalized as saying that if the researcher regresses revenue on realized weather, \( g(z) \), and the public forecast using

\[
y_t = \alpha_0 + \alpha_2 \theta_0 + \alpha_1 g(z_t) + \theta_1 \alpha_2 g(z_t) + \alpha_2 \xi_t + \nu_t.
\]

then the covariance between realized weather and the error term needs to be zero. Zero covariance between \( \nu_t \) and \( g(z_t) \) follows from the assumption that Equation (6) is well identified. The condition thus amounts to needing \( \mathbb{E}[g(z_t)\xi_t] = 0 \). Under this condition, the estimate of the direct effect, \( \alpha_1 \), will be consistent by the usual arguments for the consistency of the ordinary least squares estimator. A sufficient condition for this to hold is that the public forecaster has a weakly larger information set than the private agent. In such a case, the agent will adopt the public forecast as their private belief. Elaboration on this case can be found in Section A.4.

The adaptation effect, \( \alpha_2 \), can be identified under a substantially weaker assumption. To get correct inference on this parameter, the researcher only needs that \( \theta_1 \) be equal to 1. A sufficient condition for this to hold is that the private and public forecasts are both unbiased estimates of \( g(z_t) \). In that case, \( \hat{g}(z_t) \) will be an unbiased estimate of \( \mathbb{E}^L_{t-1}[g(Z_t)] \) as well, so \( \theta_1 = 1 \) and \( \theta_0 = 0 \). Section 3.1 provides evidence that unbiasedness is the stated goal of forecasters in the empirical setting.

This discussion highlights two important benefits of including accurate measures of agent beliefs in an estimating equation for weather effects. First, excluding a measure of beliefs will lead to omitted variable bias. This bias is straightforward to sign because the agent’s beliefs should be positively correlated with realizations of weather, so one only needs to know whether weather is positively or negatively correlated with revenue to determine whether the bias will be positive or negative. In the empirical setting, it will be shown that omitting forecasts leads to severe over-estimates of the direct effect (\( \alpha_1 \) in the context of Equation (6)).

Second, an alternative approach to measuring agent expectations that is implicitly used in much of the literature is to use average weather. When studying climate adaptation, using average weather might not provide good inference. First, climate change implies that the distribution of weather is shifting over time, so if agents are updating their beliefs about the climate, then historical averages will not be perfectly accurate proxies for agent beliefs. In cases where the relevant stochastic

\[\text{18} \]The error in this approximation can be large in extreme cases. For instance, if agents have perfect foresight and the mean of the climate process is drawn from a stochastic process with no serial correlation, then the historical average weather will have zero correlation with the expected weather this period. In general, by measuring true beliefs with error, average weather will provide attenuated estimates of adaptation and exaggerated estimates of direct effects.
variable is stationary and agents have unchanging beliefs, then adaptation as defined by Equation (3) will be zero, and the appropriate way to study adaptation would be through changes in returns to, or prices for, adaptation mechanisms. On the other hand, using contemporary averages makes the assumption that agents have, and act on, perfect foresight about average temperature. This will lead to attenuation of adaptation estimates in cases where agent beliefs do not perfectly match realized changes in climate. This method also assumes that the period over which weather is averaged is equal to the period over which beliefs about the weather are fixed. Finally, average weather cannot be used in cases where the relevant climate shifts are measured in terms of anomalies (as in the empirical setting of this study). The expected value of the process over any sufficiently long period in this case will be zero by construction, so no identifying variation in average weather will exist.

2.2.1 Violations of forecast proxy conditions

In many cases where the forecast proxy conditions are violated, the adaptation estimate will be attenuated and the direct effect will be larger in magnitude—both leading to underestimates of the relative degree of adaptation. Thus, the method presented here provides a conservative estimate of adaptation under plausible assumptions.

Maintaining the assumptions that forecasts are public and that agents are fully sophisticated but making no assumption about the relationship between the public and private forecasts, an optimizing firm’s private forecast will only differ from the public forecast if there is additional predictive power in the private forecast. In that case one should expect that \( \mathbb{E}[g(z_t)\xi_t] > 0 \), so the usual omitted variable bias formula can be applied to find that \( \text{plim} \left| \bar{\alpha}_1 \right| = \left| \alpha_1 + \alpha_2 \frac{\text{Cov}(\xi_t, g(z_t))}{\text{Var}(g(z_t))} \right| \). If \( \alpha_2 < 0 \), then the estimated coefficient will be biased upward, meaning that the direct effect will be over-estimated. As discussed above, an extreme version of this is omission of any measure of an agent’s beliefs.

Perhaps due to ensemble averaging considerations following Stein (1956) and Efron and Morris (1975), a firm or the forecaster might prefer a biased estimator. If the level of bias is constant, the bias will enter \( \theta_0 \), and the estimate of the adaptation effect will still be consistent for the true adaptation effect. The covariance between \( \xi_t \) and realized weather will no longer be zero, and the inconsistency will depend on the sign of the bias of the estimator employed by the forecaster or agent.

If the firm and forecaster information sets are partly disjoint or if the firm creates its own forecasts but with a smaller information set than the public forecaster, then one could see bias in \( \alpha_2 \). For instance, if the firm consumes its own forecast even though it is inferior to the public forecast, then the public forecast would possess...
measurement error when used in the estimating equation. In general, so long as the public forecast is positively correlated with the realized state, then unless the private agent has a reason to construct a negatively correlated forecast, using the public forecast for estimation will return the correct sign on the adaptation effect and will help reduce the omitted variable bias from ignoring adaptation.

3 Empirical setting background and data

3.1 Albacore fishing, ENSO, and ENSO forecasting

The remaining sections of the paper apply the theory from Section 2 to estimate the benefit of adaptation and direct effect of climate fluctuations on firms in the U.S. North Pacific albacore tuna fishery. Four attributes of this setting make it ideal to study adaptation. First, the fishery is affected by ENSO, an important climate phenomenon that causes changes oceanic temperatures and weather conditions (and therefore affects fishing quality). Second, for multiple decades, the fishery has relied on professional forecasts of ENSO. NOAA issues ENSO forecasts directly to albacore harvesters in the fishery, and interviews with harvesters indicate that these forecasts are utilized. The fishery is also almost entirely located in the northern Pacific Ocean, far from where ENSO conditions develop. This means that NOAA information is plausibly the primary or only source of ENSO information for these firms. Third, concerns about other confounding effects are minimal. The fishery does not suffer from congestion, is not subject to catch quotas, and the albacore population is relatively healthy (Albacore Working Group, 2014). The U.S. harvesters studied here account for a small part of the global albacore tuna output. A large portion of albacore tuna is canned and therefore storable, reducing price effects from climate variation. The primary variable cost comes from diesel fuel, a globally traded and produced commodity. Fourth, detailed logbook records of output and some inputs are required to be kept on a daily basis for each firm in the industry.

Albacore (Thunnus alalunga) typically stay in waters with sea surface temperature between 15 and 20°C (Childers et al., 2011). They also follow oceanic fronts with strong temperature gradients which limit the movement of their prey. The temperature preferences of albacore make them highly responsive to changes in climate. The preferences of the albacore have led harvesters to develop rules of thumb based on sea surface temperature and ocean conditions including water color and clarity when determining where to try to catch fish (Clemens, 1961, Laurs et al., 1977, 1984, Childers et al., 2011).

ENSO affects temperature in the North Pacific (see Figure A6) as well as oceanic
conditions like temperature gradients. These shifts make it harder for vessels to locate albacore (Fiedler and Bernard, 1987).\(^\text{19}\) ENSO, therefore, generally entails more intensive and costly search for fish. In interviews, harvesters indicate that if uncertainty about optimal fishing location is too high or if expected fishing grounds are too distant from shore, they respond by temporarily exiting the albacore fishery in order to pursue crabs and other pelagic species less affected by ENSO conditions (Wise, 2011, McGowan et al., 1998).

On average, harvesters take fishing trips that last two weeks long, but trips can last up to three months. Harvesters generally take between 1 and 2 trips per month. An ideal trip involves an initial transit to a fishing ground followed by little movement of the vessel as actual fishing occurs. Because ENSO effects are felt in the fishery as quickly as a week after equatorial temperature changes (Enfield and Mestas-Nuñez, 2000), this strategy can be disrupted by unanticipated ENSO events.

Unfortunately for the harvesters, prior to the late 1980s, ENSO was not forecastable. In fact, despite the importance of ENSO to global climate, equatorial temperature anomalies were often not even detectable prior to the deployment of the Tropical Atmosphere Ocean (TAO) array of weather buoys between 1984 and 1994 (Hayes et al., 1991).\(^\text{20}\)

Skillful forecasts of ENSO were developed starting in the mid-1980s. 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. A stated goal of the LDEO forecasting group was to produce unbiased forecasts of ENSO (Chen et al., 2000). In the late 1980s, NOAA’s Climate Prediction Center (CPC) began to produce a statistical forecast of ENSO based on Canonical Correlation Analysis (CCA).

Starting in June 1989, NOAA began publicly issuing 3-month ahead ENSO forecasts in the Climate Diagnostics Bulletin, a publication of global climate information and medium term climate forecasts. The Climate Diagnostics Bulletin initially reported the LDEO1 forecast, and forecasts from additional forecasting groups were

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\(^{19}\) Lehodey et al. (2003) shows that, in addition to spatial dislocation, Pacific albacore recruitment tends to fall after El Niño periods, indicating that there might be temporal spillovers between ENSO and catch in the fishery. I check this in Table 3 and rule it out as an explanation of the main results I find.

\(^{20}\) NOAA’s history of ENSO measurement notes, “Development of the Tropical Atmosphere Ocean (TAO) array was motivated by the 1982-1983 El Niño event, the strongest of the century up to that time, which was neither predicted nor detected until nearly at its peak.” [http://www.pmel.noaa.gov/tao/proj_over/taohis.html](http://www.pmel.noaa.gov/tao/proj_over/taohis.html)
incorporated as they were published, starting with the CCA forecast in November 1989.\footnote{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/CDB_Archive.html/CDB_archive.shtml}} By the end of the sample in the mid 2010s, the Bulletin published 21 ENSO forecasts on a monthly basis. See Appendix B.1 for more information on the content of the Bulletins. Analyses of forecast accuracy and performance over time can be found in Barnston et al. (2010, 2012).

At nearly the same time that ENSO forecasts were being created, NOAA started a program called CoastWatch, first launched in 1987, to disseminate forecasts, satellite imagery, and other data to coastal businesses and individuals. ENSO forecasts from the Climate Diagnostics Bulletin were incorporated in the CoastWatch releases, and personal correspondence with albacore harvesters indicates that CoastWatch forecasts were routinely posted at albacore fishing ports along the Pacific coast. Even today, private companies selling weather forecasts and satellite imagery to the albacore fishery repackage the NOAA ENSO forecasts.\footnote{For instance, SeaView Fishing, a private firm used by the fishers that I spoke to, simply links to NOAA’s ENSO forecast website for predictions of El Niño and La Niña (SeaView Fishing, 2019).}

For this paper, I focus on the effects of the 3-month-ahead ENSO forecast. The use of this forecast is primarily due to the history of NOAA’s public forecast releases. The 3-month-ahead forecast was the first one issued by NOAA and therefore has the longest history. This choice of horizon is also practical: the Bulletin forecasts are typically released a month after they have been generated, so a three month ahead forecast is, practically, a one or two month ahead forecast from the perspective of the end user. Given the timing of ENSO effects being felt in the North Pacific and typical trip length, this forecast horizon is likely to be the relevant one for fishing decisions because fishing trips typically last between two weeks and one month.\footnote{As I discuss further below, the choice of horizon is relatively unimportant if the researcher is only interested on separately identifying the benefit of adaptation and direct effect. Use of multiple forecast horizons can be helpful for understanding the timing of adaptation.}

## 3.2 Dataset construction

For estimation, data on equatorial and North Pacific sea surface temperatures, ENSO forecasts, vessel-level fish catch, and relevant prices need to be combined. Here, I briefly describe each dataset used in the analysis. Summary statistics for the variables can be found in Table 1 and more details about dataset construction can be found in the Appendix.

ENSO is typically measured using temperature anomalies in the equatorial Pacific Ocean. NOAA’s Climate Prediction Center (CPC) publishes monthly average
temperature anomalies in what is known as the Niño 3.4 region of the Pacific, a rectangular area ranging from 120°W-170°W longitude and 5°S-5°N latitude. Anomalies are calculated with respect the thirty-year average temperature. This study uses the 1971-2000 average. Following Trenberth (1997) and NOAA, I classify El Niño and La Niña events based on five consecutive months where the three month moving average of the Niño 3.4 index is greater than 0.5°C for El Niño or less than −0.5°C for La Niña.

Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly number of fish caught</td>
<td>159.10</td>
<td>786.88</td>
<td>159,618</td>
</tr>
<tr>
<td>Monthly catch (tons)</td>
<td>0.87</td>
<td>4.75</td>
<td>159,618</td>
</tr>
<tr>
<td>Niño 3.4 index</td>
<td>0.12</td>
<td>0.93</td>
<td>159,618</td>
</tr>
<tr>
<td>3 month-ahead Niño 3.4 forecast</td>
<td>0.09</td>
<td>0.73</td>
<td>159,618</td>
</tr>
<tr>
<td>Vessel length (m)</td>
<td>16.68</td>
<td>5.84</td>
<td>151,411</td>
</tr>
<tr>
<td>Fuel price (2001 $/gal)</td>
<td>1.60</td>
<td>0.77</td>
<td>156,571</td>
</tr>
<tr>
<td>Albacore price (2001 $/lb)</td>
<td>1.19</td>
<td>0.24</td>
<td>130,409</td>
</tr>
</tbody>
</table>

Notes: Averages, standard deviations and number of observations for primary variables in the dataset are shown for the estimation sample (September 1989 to December 2016). Observations are at the vessel-month level.

Data on ENSO forecasts come from two sources. Public ENSO forecasts have been issued as part of NOAA’s Climate Diagnostics Bulletin since June 1989. These are usually published as point forecasts for the coming few months or seasons, along with observations of ENSO from recent months. I digitized forecasts from these bulletins for the period from 1989 until 2002. In 2002, the International Research Institute for Climate and Society (IRI) began keeping records of publicly issued ENSO forecasts, and Anthony Barnston at IRI provided me with digital records for the period from 2002 to the present. For the analysis, I use the 3-month-ahead forecasts, for reasons discussed in Section 3.1. Because I use 3-month-ahead forecasts, my sample begins in August 1989 (the target date of the first operational forecast issued in June but using data through May). The sample ends in December 2016. More details on the construction of the historical forecast dataset can be found in Appendix B.1.

The data for the albacore fishery consist of daily, vessel-level logbook observations of U.S. troll vessels. The National Marine Fisheries Service (NMFS) requires the vessel operator to maintain accurate logbook records in order to access the fishery. All

fishing days are observed, with additional information provided for some transiting and port days (these latter data do not appear to be consistently reported). For each fishing day, the logbooks report the number of fish caught, the weight of fish, a daily location record (latitude and longitude), the sea surface temperature, the number of hours spent fishing (versus steaming, baiting, or doing other activities), and the number of troll lines used. At the trip-level, the logbooks report vessel length, departure and arrival port, and total weight of catch for the trip. Landing port is matched to the Pacific Fisheries Information Network (PacFIN) database on annual albacore sale prices for 1989 to 2016. Only ports in the continental U.S. are in the PacFIN database, so albacore prices are only available for those landings (about 78% of the primary estimation sample).

The vessels in the sample use #2 marine diesel fuel. Where available, the price for this fuel is used for cost calculation, but the price for this exact fuel type is not available over the full sample. From 1989 to 1999, monthly, state-level average prices for diesel, gasoline, or number 2 distillate (the class of fuel containing diesel and heating oil) are available from the Energy Information Agency “Retailers’ Monthly Petroleum Product Sales Report.” Different states have records for diesel fuel prices starting at different dates, but by 1995, all states in my sample report diesel prices. For periods prior to 1995 when a state does not report diesel prices, number 2 distillate prices are used if they are available. Over the sample where both diesel and distillate prices are observed, the values correspond closely. If neither diesel nor distillate prices are available, then gasoline prices are used after accounting for seasonal differences between gas and diesel. From 1999 to the end of the sample, monthly, port-level prices for marine diesel are available from the Pacific States Marine Fisheries Commission EFIN database. See Appendix B.3 for further details. All prices have been deflated to 2001 dollars using the monthly core consumer price index from the U.S. Bureau of Labor Statistics available from the Federal Reserve Bank of St. Louis’ FRED database.

Finally, full costs, expenditures, and revenues for a panel of 35 albacore harvesters were recorded from 1996 to 1999 in the National Marine Fisheries Service/American Fisheries Research Foundation (NMFS/AFRF) Cost Expenditure Survey. These are the best available data for costs in this fishery, and the fraction of costs attributable to fuel is calculated based on this sample.

Available online from www.psmfc.org/efin/data/fuel.html.
4 Empirical strategy

The conceptual models show that to estimate the effect of ENSO on the fishery one can regress revenue on forecasts and realizations of ENSO, as in Equation (6). In the primary results, I will estimate linear specifications regressing revenue or output on the one-month lag of ENSO and its forecast. The lag between changes in ENSO in the equatorial Pacific and the effects being felt in the North Pacific suggests that the first lag of ENSO is what affects the fishery.

Linearity has important advantages of simplicity of interpretation and estimation. Semiparametric tests using pre-forecast data also support the use of a linear estimating equation. I observe logbook records starting in 1981, prior to the existence of public forecasts. Under the assumption that month-to-month changes in ENSO were unforecastable, estimating the effect of ENSO on output in the period prior to the introduction of forecasts provides evidence on the shape of \( g \) without needing to account for agent beliefs.\(^{26}\) Figure A2 implements this test, showing the semiparametric relationship between the one-month lag of ENSO conditional on baseline controls (discussed below) and output conditional on the same covariates. Importantly, these controls include additional lags of ENSO. The figure shows that the relationship between ENSO and output in this period was linear.

Lagged effects plus linearity imply that

\[
g(z_{t-1}) = \gamma_{\ell,0} + \gamma_{\ell,1} z_{t-1} \tag{8}
\]

where \( \gamma_{\ell,0} \) is a positive constant large enough to induce entry into the fishery, \( z \) is a measure of ENSO, and \( \gamma_{\ell,1} \) captures the effect of temperatures last month in the equatorial Pacific on the fishery. If warmer temperatures are harmful for the fishery, then \( \gamma_{\ell,1} \) will be negative. If cooler temperatures are harmful, then \( \gamma_{\ell,1} \) will be positive.

The estimating equation to identify the benefit of adaptation and direct effect of ENSO is

\[
y_{it} = \beta_1 z_{t-1} + \beta_2 \hat{z}_{t-1} + \sum_{k=1}^{K} (\alpha_{z,k} z_{t-1-k} + \alpha_{\hat{z},k} \hat{z}_{t-1-k}) + \delta_{1,i} + \delta_{2,y(t)} + \delta_{3,m(t)} + \varepsilon_{it} \tag{9}
\]

\(^{26}\)As discussed in the background section, in the mid 1980s NOAA forecasters believed that skillful monthly horizon forecasts of monthly changes in ENSO were impossible. Therefore, the assumption that firms were unable to forecast deviations in ENSO relative to recent ENSO realizations might be reasonable.
where $y_{it}$ is output or revenue for vessel $i$ at time $t$ (time is measured in months). The two primary variables of interest are $z_{t-1}$, the realized value of the Niño 3.4 index the previous month, and $\hat{z}_{t-1}$, the three-month ahead forecast of ENSO. Control variables are vessel, year, and month fixed effects as well as two lags of both the Niño 3.4 index and the three-month ahead forecast in the baseline specification. Finally $\varepsilon$ is a stochastic error term.

Adaptation is measured by the magnitude of the $\hat{z}$ coefficient relative to that of the $z$ coefficient. The larger the magnitude of $\beta_2$ relative to $\beta_1$, the greater the adaptation because it means more of the effect of ENSO is operating through changes in actions by the agents. The effect of ENSO net of forecasts captured by $\beta_1$ is the direct effect that agents are unable to adapt away. The effect that agents control is given by $\beta_2$.

5 Results for ENSO effects and adaptation

5.1 Estimates of adaptation and direct effect

Table 2 shows results from implementing the primary identification strategy. Each column shows estimates of versions of Equation (9) using monthly data. The dependent variable in the first two columns is the number of fish caught per month by each vessel. In the third and fourth columns it is the revenue for each vessel. All dependent variables are standardized to have mean 0 and standard deviation of 1. The primary explanatory variables are listed in the left column, and control variables are indicated below the coefficient estimates. The standard errors in all models are spatial-temporal heteroskedasticity and autocorrelation robust, using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation (Conley, 1999).

The first and third columns regress catch and revenue on measures of the realized strength of the one-month lag of the Niño 3.4 index (coefficient estimates in the row Niño 3.4) but do not include forecasts. The results illustrate the omitted variable bias that occurs if forecasts are not included in the regression. The coefficients on realized Niño 3.4 indicate that ENSO has a moderate, negative effect on catch and

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27 As discussed above, I use the three-month ahead forecast because it has the most complete data series and because it likely matches the decision-making horizon of the firms (see Section 3). Given that the focus is on estimating the overall benefit of forward-looking adaptation, however, the exact horizon of the forecast is not crucial. Forecasts at different horizons are positively correlated, so they will recover related estimates. The crucial distinction is between forecasts and realizations.

28 Revenue information is not available for the full dataset, either because the logbook record is missing information on the weight of the fish caught or because the vessel offloads fish at a port outside of California, Washington, or Oregon where albacore price is observed. The results reported in this table use imputed weight where weight is missing. The effect of this imputation is assessed in robustness Table A1.
Table 2: Effect of ENSO on Standardized Output and Revenue

<table>
<thead>
<tr>
<th></th>
<th>(1) Catch</th>
<th>(2) Catch</th>
<th>(3) Revenue</th>
<th>(4) Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.086***</td>
<td>-0.026</td>
<td>-0.10***</td>
<td>-0.086***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.024)</td>
<td>(0.017)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.29***</td>
<td></td>
<td>-0.14***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td></td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>Lagged controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Vessel FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
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<td>1,214</td>
<td>1,214</td>
</tr>
<tr>
<td>Observations</td>
<td>159,602</td>
<td>159,602</td>
<td>131,296</td>
<td>131,296</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating equation (9) on monthly data. The dependent variable in each model is indicated at the top of the column. All dependent variables are standardized. Catch is the total number of fish caught per month. Revenue is the total ex-vessel value of catch. Additional controls are indicated at the bottom and are lagged Niño 3.4 index, lagged forecasts (Columns 2 and 4), and fixed effects for vessel, year, and month. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

An increase in the Niño 3.4 index from 0 to 1 (moving from normal conditions to a moderately strong El Niño) reduces catch and revenue by about 0.1 standard deviations.

Without including forecasts, however, these result do not give a complete or accurate picture of the effects of ENSO on the fishery. Columns 2 and 4 add the first lag of the three-month ahead forecast of ENSO (row Niño 3.4). The two coefficients in the table correspond to $\beta_1$ and $\beta_2$ from Equation (9).

One can see that predicted changes in ENSO have a much larger effect on output and revenue than do realized changes. An increase in the forecast leads to a drop in output roughly ten times larger than a comparable change in realized ENSO. The second and third lags of the forecast are also added as controls. All specifications include vessel, year, and month fixed effects as well as the second and third lag of the realized Niño 3.4 index.
effect of forecasts on revenue is roughly twice the size of the effect of realized ENSO.\textsuperscript{30}

In the context of the model, the effect of forecasts identifies the benefit of forward-looking adaptation. Why is the benefit of adaptation negative in this case? As will be seen in the mechanism analysis below, firms adapt by reducing their costs of production during periods with bad ENSO conditions. Because costs are saved, the “costs of adaptation” are positive while the “benefits of adaptation” are negative. Another way to interpret the coefficient is to think about reductions in the Niño 3.4 index. These better climate conditions will lead to improved output and revenue at the expense of higher costs of production. In this case, adaptation is taking advantage of improved climate rather than buffering the firms from a worsened climate.

The first coefficients from columns 2 and 4 show that conditional on forecasts, the effect of realizations of ENSO is also reduced relative to the regressions that omit forecasts. The effect on output in particular is overstated by a factor of 3 when forecasts are omitted. This illustrates one of the biases in climate damage estimation that can result from ignoring adaptation. In the context of the model, the effect of realized Niño 3.4 identifies the direct or net-of-adaptation effect of climate variation. Omitting forecasts would lead to a substantial over-estimate of the direct effect in this case.

Another source of bias is also apparent. The total effect of ENSO—the direct effect plus the benefit of adaptation—is underestimated by a factor of nearly 4. Summing the effects from both realized and forecasted ENSO, moving from normal conditions to a moderate El Niño (Niño 3.4 index of 1) leads to a 0.32 standard deviation decline in output, on average, for a vessel. If adaptation is costly, the large total effect has bearing on welfare analysis. Reducing the need for adaptation would reduce costs for firms.

The amount of forward-looking adaptation, captured by the effect of forecasts, relative to the total effect gives a summary measure of the effectiveness of adaptation in this setting. In the context of the model, this value is $B(A)$, the marginal benefit of adaptation, divided by the total effect $\frac{dE[y^*]}{dE[g(Z)]}$. I denote the value by $B_n(A)$ because it is the normalized benefit of adaptation. With a linear specification, this value is simply $\frac{\beta_2}{\beta_{1}+\beta_{2}}$. For output, $B_n(A)$ is 0.92 (95% confidence interval of 0.77 to 1.06), indicating that 92% of the total effect of ENSO on output is due to adaptation. For revenue, $B_n(A)$ is 0.63 (95% CI of 0.46 to 0.80).\textsuperscript{31} In both cases, adaptation is well above zero.

\textsuperscript{30}Table 4 shows that the difference in magnitudes between the output and revenue effects is largely explained by sample differences. Prices and catch weight are not observed for all vessels.

\textsuperscript{31}Standard errors calculated using the delta method.
5.2 Robustness

Table 3 checks the robustness of the linear output estimates from Table 2 Column 2 to changes in controls. In Column 1 the separate vessel and year fixed effects are replaced by a set of vessel-year fixed effects. In Column 2 the vessel and month fixed effects are replaced by vessel-month fixed effects. These more flexible controls do not appreciably change inference. Column 3 adds vessel-specific linear trends. Trends could be important because catch is rising, on average, over time, and forecast quality is also changing over time (Appendix Figure A5). Again, however trends have a negligible effect on inference.

Table 3: Robustness to Covariates

<table>
<thead>
<tr>
<th></th>
<th>(1) Vessel by year FEs</th>
<th>(2) Vessel by month FEs</th>
<th>(3) Vessel trends</th>
<th>(4) Niño 3.4 ( t - 12 )</th>
<th>(5) Niño 3.4 6 lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.025</td>
<td>-0.026</td>
<td>-0.026</td>
<td>-0.034</td>
<td>-0.043</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.019)</td>
<td>(0.024)</td>
<td>(0.024)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.29***</td>
<td>-0.24***</td>
<td>-0.29***</td>
<td>-0.28***</td>
<td>-0.24***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.027)</td>
<td>(0.034)</td>
<td>(0.040)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>SEs</td>
<td>Spatial</td>
<td>Spatial</td>
<td>Spatial</td>
<td>Spatial</td>
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</tr>
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<td>Observations</td>
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<td>159,602</td>
<td>149,967</td>
<td>154,557</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating versions of equation (9) on monthly data. The dependent variable in each model is standardized monthly number of fish caught. In addition to the listed variables, all models contain vessel, year, and month-of-year fixed effects as well as two additional lags of realizations and forecasts of the Niño 3.4 index unless otherwise noted. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation, unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Lehodey et al. (2003) raises the possibility that ENSO in one year might cause a fall in recruitment of fish into the harvestable stock in the next year. Column 4 shows that controlling for the level of the Niño 3.4 index from a year prior to the current month, however, does not indicate that conditions a year ago have strong bearing on adaptation to changes in ENSO this year. The conclusion of Lehodey et al. (2003) is strongly supported by the data, with year-ago ENSO values having a comparable effect on catch to the contemporaneous measures.

Finally, Column 5 shows robustness to including additional lags of both Niño 3.4 and forecasts. The baseline specification includes the first, second, and third lag of
these measures (with the first lag being the variable of interest). Accounting for serial correlation is important for isolating news from the forecasts and ensuring that estimates are not polluted by persistent effects of past realizations. Column 5, which includes 6 lags of both measures, is reassuring that changing the lag length will not alter the baseline results.

**Table 4: Robustness to Sample, Clustering, and Specification Changes**

<table>
<thead>
<tr>
<th></th>
<th>(1) Catch</th>
<th>(2) Catch</th>
<th>(3) Catch</th>
<th>(4) Catch</th>
<th>(5) Catch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.026</td>
<td>-0.048**</td>
<td>-0.018</td>
<td>-0.0087</td>
<td>-0.0089</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.020)</td>
<td>(0.024)</td>
<td>(0.026)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.29***</td>
<td>-0.17***</td>
<td>-0.28***</td>
<td>-0.37***</td>
<td>-0.26***</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.032)</td>
<td>(0.034)</td>
<td>(0.039)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Catch t − 1</td>
<td>0.51***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Covariates</th>
<th>Baseline</th>
<th>Baseline</th>
<th>Baseline</th>
<th>Baseline</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEs</td>
<td>Y-M cluster</td>
<td>Spatial</td>
<td>Spatial</td>
<td>Spatial</td>
<td>Spatial</td>
</tr>
<tr>
<td>Sample</td>
<td>Baseline</td>
<td>Observe revenue</td>
<td>Latitude</td>
<td>Drop</td>
<td>Baseline</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&lt; 46°</td>
<td>1997-2001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>159,602</td>
<td>131,296</td>
<td>157,424</td>
<td>128,546</td>
<td>157,916</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating versions of equation (9) on monthly data. The dependent variable in each model is standardized monthly number of fish caught. In addition to the listed variables, all models contain vessel, year, and month-of-year fixed effects as well as two additional lags of realizations and forecasts of the Niño 3.4 index unless otherwise noted. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation, unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table 4 shows variations in the standard error calculation method, changes in sample, and one additional variation in specification. Column 1 clusters standard errors at the year-month level. ENSO is a group shock, and forecasts are released each month, so this level of clustering more closely matches the level of aggregation of the exogenous shock. Inference is less precise in this case, but the forecast effect is still significant at the 1% level. The spatial standard errors are preferred for the baseline specification, however, because ENSO does have local effects on fishing conditions that vary smoothly over space (see Appendix Figure A6), so year-month clustering is likely to be too conservative.

Column 2 excludes observations for which I do not observe revenue. One can
see that the larger direct effect and smaller benefit of adaptation estimated using revenue in Table 2 appears to largely be a result of differences in sample rather than differences between output and revenue. The model assumed that output prices were not affected by ENSO, so this result is reassuring. A more direct test, reported in Table A9, also shows that output prices are not significantly correlated with ENSO.

Column 3 excludes observations near Canadian fishing grounds. Congestion in the fishery is, in general, low. The exception commonly noted during interviews was due to Canadian vessels near the northern edge of the fishery. Excluding this area has a negligible effect on the estimates. Column 4 drops the period in the late 1990s and early 2000s with a historically large El Niño event. The results are largely unchanged whether including or excluding this period. Another large ENSO event occurred at the end of the sample, and excluding this period also has little effect.

Columns 4 adds the one-month lag of catch. The baseline estimates use two year lags to account for autocorrelation in the residuals. Monthly autocorrelation might also be important. Including this control does not appreciably change the adaptation effect. The direct effect falls slightly. Multiplicative separability for the linear model is not reported in the robustness tables. But in unreported estimates, the interaction between Niño 3.4 and the forecast is zero in the linear model.

Some interpolation was performed to arrive at the revenue observations. This incompleteness comes from two sources. First, albacore prices are only observed for a subset of U.S. ports. Vessels missing albacore price are simply excluded from the sample when estimating revenue or profit effects because it is unknown by me whether prices in non-U.S. ports follow the same trends as prices in U.S. ports. Among the remaining vessels, not all observations contain records of the weight of fish caught that day. For those observations, I impute weight in one of two ways. First, if the logbook records the total weight of fish caught during the trip, I multiply the number of fish caught that day by the average weight of fish for the trip. If trip-level weight is missing, then I interpolate weight based on catch of other vessels fishing at the same time as the missing observation. Table A1 investigates whether this interpolation procedure leads to bias in the estimates. Overall, the results show that the interpolation procedure is not leading to substantive changes in estimates, in part because only about 2,000 observations are interpolated.

32 All vessels in the dataset are based in the U.S. but will sometimes offload at non-U.S. ports.
6 Adaptation mechanisms

This section explores how the firms in this fishery achieve the high rates of adaptation estimated in the previous section. From the main results, it is clear that the mechanisms must be cost-saving. Firms suffer output and revenue losses due to the forecasts, so they must be saving on cost by engaging in behaviors to make the output and revenue loss worthwhile. The results below show that firms do indeed engage in multiple cost-saving measures both on the intensive margin—after choosing to go out an fish—and on the extensive margin when choosing whether to take a fishing trip in a given month.

The results below are not necessarily exhaustive of all the mechanisms these firms have employed to adapt. One of the benefits of the methodology in this paper is that the researcher need not know about or have data on all potential adaptation mechanisms to still gain an understanding of the benefit of adaptation. Instead, the results are corroborating evidence that firms are primarily adapting by saving costs and reducing their exposure to downside risks.

6.1 Adaptation mechanisms conditional on fishing

Table 5 shows estimates for the effect of anticipated and unanticipated changes in ENSO on choices made while fishing. The outcomes listed in the table are primarily determined on a daily or trip-level frequency. Overall, the results show that if a captain chooses to go fishing when they anticipate worse conditions, they take a variety of actions during the trip to reduce costs. If the poor conditions are unanticipated, the firm, if anything, engages in slightly more costly behavior.

Column 1 of Table 5 looks at the temperature of the water in which the captain chooses to fish. Historically, fishers employed a heuristic that albacore congregate most in water around 17 or 18°C. The dependent variable is the absolute difference between actual water temperature (as recorded in vessel logbooks) and 17.5°C. The results are imprecise and small, indicating that captains are not strongly selecting their fishing locations based on ENSO. The point estimates suggest that captains are hewing closer to the heuristic when ENSO is anticipated than when it is not.

The dependent variable in column 2 is hours of fishing per day. Good or bad fishing conditions could lead to more hours of fishing. If the vessel’s hold is filled quickly, then fishing hours would go down. If fishing is poor, the crew may continue to fish longer to make up for the shortfall or may stop fishing earlier to change fishing locations. In response to anticipated ENSO, harvesters decrease their hours fished per day by just over 5%. Whether this is due to poor fishing conditions or not, this
Table 5: Intensive-Margin Mechanisms

<table>
<thead>
<tr>
<th></th>
<th>(1) Temperature choice error</th>
<th>(2) Hours per day Fishing</th>
<th>(3) Fishing lines</th>
<th>(4) Movement extensive</th>
<th>(5) Movement intensive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>0.019</td>
<td>0.12</td>
<td>0.16</td>
<td>-8.66</td>
<td>27.0</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.37)</td>
<td>(0.31)</td>
<td>(9.75)</td>
<td>(52.0)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.029</td>
<td>-0.70***</td>
<td>-1.16***</td>
<td>-188.1***</td>
<td>-407.8***</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.20)</td>
<td>(0.18)</td>
<td>(18.8)</td>
<td>(93.3)</td>
</tr>
<tr>
<td>Dep. var. mean</td>
<td>0.99</td>
<td>12.13</td>
<td>10.71</td>
<td>155.89</td>
<td>1,086.74</td>
</tr>
<tr>
<td>Baseline FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>16,885</td>
<td>14,044</td>
<td>17,269</td>
<td>159,602</td>
<td>17,320</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating versions of equation (9) on monthly data. The dependent variable in each model is indicated at the top of each column. Additional controls are indicated at the bottom and are fixed effects for vessel, year, and month. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

reducing in hours worked per day entails a reducing in intensive-margin effort.

One of the primary variable costs in this industry is labor, and one of the important shortcomings of the logbook records is that labor on the vessel is not recorded. The best available proxy measure is the number of fishing lines used each day. Harvesters in this dataset use pole and line fishing—a relatively labor intensive but sustainable method where individual fishing lines are used to catch each fish. Operating more lines in this fishery requires either more effort or more labor. The results show that about 1 fewer fishing line is used per day if ENSO is anticipated than if it is not. If harvesters are using fewer lines to save on labor costs, this could represent an important overall reduction in variable costs.

Another major source of variable cost for the vessels is the burning of fuel during transit and fishing. Table 5 Column 4 shows the effect of ENSO on vessel movement. Section B.4 provides details on this measure, but the basic method is to use the latitude and longitude records each day to calculate day-to-day movement. Such a calculation will miss intra-day movement. The results indicate that harvesters move less if they anticipate worse ENSO conditions. As will be shown below, this result is partly driven by the decision of whether to enter the fishery in a given month. Column 5 shows that even conditional on this decision, harvesters still move less if

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33This is in contrast to methods like long-lining where a single, long fishing line might have hundreds or thousands of baited hooks.
they anticipate bad conditions. In contrast, if bad conditions arrive unexpectedly, they move more, perhaps to compensate for the worse conditions.

Many of the adaptations available to albacore harvesters can only be implemented between trips. In the extreme case, things like characteristics of the boat hull are fixed once a trip has begun. Labor is determined between trips as well, although that labor can be employed more or less intensively during the trip. Hull length (unsurprisingly) does not change in response to ENSO. One adaptation that is open to the harvesters on a trip-level frequency and does appear to change with ENSO is the length of the trip and the number of overall fishing days in a month, as shown in Table 6.

<table>
<thead>
<tr>
<th></th>
<th>(1) Fishing days</th>
<th>(2) Transiting days</th>
<th>(3) Trips per month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>0.00018</td>
<td>0.033</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.085)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-3.52***</td>
<td>0.085</td>
<td>-0.087**</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.16)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Dep. var. mean</td>
<td>10.6</td>
<td>0.86</td>
<td>1.42</td>
</tr>
<tr>
<td>Baseline FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>17,320</td>
<td>17,320</td>
<td>17,320</td>
</tr>
</tbody>
</table>

**Notes:** The table shows results from estimating versions of equation (9) on monthly data. The dependent variable in each model is indicated at the top of each column. Additional controls are indicated at the bottom and are fixed effects for vessel, year, and month as well as two additional lags of realizations and forecasts of the Niño 3.4 index. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Column 1 shows that vessels fish fewer days per month given an unexpected change in ENSO. The magnitude is substantially larger than the tight zero effect for realizations of ENSO. As far as can be discerned from the data, there does not seem to be an effect of ENSO on transiting days, which are days away from port without any reported fishing. Transiting is not always reporting in the logbook records, however, so the results should be interpreted with caution. Finally, Column 3 shows that trips per month also slightly fall when a higher Niño 3.4 index is anticipated. Harvesters take about 1 and a half trips per month, and they take about 6% fewer trips if they anticipate adverse conditions. In contrast, there is a small and insignificant increase
in trips per month in response to realization of ENSO.

6.2 Entry and exit across months

The main results from Table 2 show adaptation that is occurring both between fishing trips and once a vessel is out fishing. Table 7 investigates the decision of whether or not to go fishing at all in a given month. The dependent variables in these models are short-run measures of entry and exit. Fish this month is an indicator equal to one if the vessel is both in the fishery and actively engaged in fishing for albacore. Exit if fishing is equal to 1 the month a vessel exits the fishery after having fished the previous month and is 0 otherwise. The estimates are from linear probability models with spatial HAC robust standard errors and all baseline covariates. Fixed effects logit models give similar estimates for the effect of forecasts, but show no significant effects from realizations of ENSO.

Table 7: Mechanisms: Entry and Exit

<table>
<thead>
<tr>
<th></th>
<th>(1) Fish this month</th>
<th>(2) Exit if fishing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.00070</td>
<td>-0.019***</td>
</tr>
<tr>
<td></td>
<td>(0.0034)</td>
<td>(0.0023)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.072***</td>
<td>0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.0067)</td>
<td>(0.0047)</td>
</tr>
<tr>
<td>Baseline controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>159,602</td>
<td>159,602</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating versions of equation (9) on monthly data. The dependent variable in each model is indicated at the top of the column. Additional controls are indicated at the bottom and are fixed effects for vessel, year, and month as well as two additional lags of realizations and forecasts of the Niño 3.4 index. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

The entry results show that vessels are less likely to be active in the fishery if ENSO is forecasted to be worse. This result helps explain the drop in output associated with increases in ENSO and also bolsters the movement results which indicated that some of the movement cost avoidance was done simply by not entering the fishery in a given month. Realized changes in ENSO conditional on forecasts do not have the
same effect, with a precisely estimated zero effect from realizations of ENSO on the entry decision.

The short-run exit decision is not as strongly related to ENSO. This is consistent with interviews with fishers indicating that on a normal fishing trip, a captain will try to continue fishing in order to fill the hold even if the fishing is going poorly. This type of behavior might make exit less responsive to climate shocks. One does see that vessels are slightly more likely to exit if they anticipate bad conditions—again saving on costs—and slightly less likely to exit if the bad conditions are unanticipated—possibly because they need to stay out longer to fill their hold.

The vessels are unlikely to be idle during months when they are not actively participating in the albacore fishery. Wise (2011) reports that many fishers also harvest crab and other species during non-albacore-fishing months. Under the assumption that fishing for these other species is not ENSO-sensitive, then welfare calculations based on the adaptation rates calculated in this paper are unaffected by this behavior.

6.3 Net Revenue

Measuring adaptation with output and revenue, as is done in the previous section, is convenient from the standpoint of data availability. If profit is continuous in all adaptation mechanisms, then an application of the envelope theorem shows that the effect of adaptation on profit is zero on the margin. In this case, estimates using profit as the dependent variable can return the direct effect of weather but not an explicit measure of the value of adaptation. Using revenue as the dependent variable will allow for the identification of the marginal benefit of forward-looking adaptation, and this adaptation measure will be equal to the marginal cost of adaptation. In such a model, estimates of the benefits of adaptation thus also provide estimates of the costs of adaptation, a method employed recently by Carleton et al. (2018).34

One consequence of the profit-neutrality of intensive margin adaptation is that the effect of forecasts on profit should be zero. The logbook data do not provide details on many of the inputs necessary to calculate full profit measures in this empirical setting. In particular, there are no measures of vessel maintenance or the wages paid to crew. The one input that can be consistently calculated is movement during fishing trips. To arrive at movement costs, I multiply movement by the average real price of fuel, based on port-level surveys. Vessel engine characteristics are unavailable, but for

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34 Using revenue instead of profit might also be necessary in cases where a substantial portion of the adaptation mechanisms are discrete. In such a case the benefits of adaptation can be substantially larger than the costs and the envelope theorem will no longer help identify direct effects even when using profit (Guo and Costello, 2013, Lemoine and Traeger, 2014).
Table 8: Effect of ENSO on Net Revenue

<table>
<thead>
<tr>
<th></th>
<th>(1) Fuel cost</th>
<th>(2) Revenue</th>
<th>(3) Net revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.026</td>
<td>-0.086***</td>
<td>-0.085***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.019)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.20***</td>
<td>-0.14***</td>
<td>-0.090***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.032)</td>
<td>(0.033)</td>
</tr>
</tbody>
</table>

Baseline controls: Yes, Yes, Yes
Observations: 131,296, 131,296, 131,296

Notes: The table shows results from estimating equation (9) using monthly data. The dependent variable is standardized fuel cost in Column 1, standardized monthly total revenue in Column 2, and standardized revenue net of movement costs in Column 3. Additional controls are indicated at the bottom and are fixed effects for vessel, year, and month as well as two additional lags of realized and forecasted Niño 3.4 index. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

vessels with known length, the average fuel consumption per kilometer conditional on vessel size is calculated from the NMFS/AFRF Cost Expenditure Survey and used to scale the fuel consumption. Fuel consumption for all other vessels is based on the unconditional average rate. The Cost Expenditure Survey shows that fuel costs represent 10 to 20% of the variable cost of running an albacore vessel, so the resulting costs are scaled to constitute 20% of observed revenues on average.

Table 8 compares the effect of forecasted and realized ENSO on fuel costs, revenue, and revenue net of movement costs for a consistent sub-sample of observations where net revenue and fuel costs are observed. As expected from the movement results in Section 6.1, fuel costs decline substantially when ENSO is anticipated. Column 2 reproduces the estimates from Table 2 for ease of interpretation. Column 3 shows that, as predicted, the magnitude of the effect of forecasted ENSO on net revenue is smaller than the effect on revenue.\(^{35}\) The effect of realized ENSO is the same for both variables.

\(^{35}\)These changes in net revenue are due to changes in firm behavior rather than through changes in albacore or fuel prices. Changes in ENSO do not have a significant effect on albacore or fuel prices, as shown in Table A9.
7 Learning and risk

7.1 Risk aversion

The theoretical model assumes that firms are solely maximizing profit. For many settings, including small-scale firms like fishing vessels, risk aversion by the vessel owner might also play an important role in decision making under uncertainty. Rosenzweig and Udry (2014) use forecasts of monsoon rain in India to investigate risk aversion in agriculture and the value of weather insurance. Adopting the reduced form of the estimating equation from that paper allows for a test of risk aversion in this setting. The expanded estimating equation becomes

$$y_{it} = \beta_0 + \beta_1 z_{t-1} + \beta_2 \hat{z}_{t-1} + \beta_3 \hat{z}_{t-1} \text{qual}_{t-1} + x_{it}' \alpha + \varepsilon_{RA,it}$$ (10)

where the new variable qual is a measure of the \textit{ex ante} quality of the forecast. All of the baseline controls have been denoted by \(x\). The intuition for this estimating equation is that the quality of the forecast matters for a risk averse agent when he or she is making input decisions because the quality measures how much uncertainty the forecast resolves. If the agent is risk averse, the quality of the forecast will be a moderating variable for the effect of the forecast on output. Under the maintained assumption that forecasts only affect inputs, this leads to a modification of the baseline estimating equation where forecast quality is interacted with the forecast terms.

I measure \textit{ex ante} forecast quality in two ways. First, I calculate the average skill from the prior 6 months. Skill is the exponential of the log of 0.5 times the squared error of the three-month-ahead forecast divided by the squared error of a persistence forecast. See Figure A5 for the time series evolution of monthly skill. This measure is a version of the Brier skill score modified in two ways (Hamill and Juras, 2006). First, a value of 0.5 indicates equal accuracy between a simple persistence forecast and the actual forecast. Second, all values of skill lie between 0 and 1. A value of this measure at 1 means that the forecast is perfectly accurate. Numbers below 0.5 mean that the forecast is inaccurate relative to a persistence forecast.

Theory predicts that a risk-averse agent will adapt more if skill is higher. The results in Table 9 Column 1 show that risk preferences are a potentially important factor. Harvesters adapt substantially more when skill is higher. The interaction between forecasts and skill is negative, so the benefit of adaptation is larger relative to the direct effect as skill goes up.

The second measure of quality is the standard deviation of the forecast plume in the prior 6 months (\textit{Ensemble sq. error}). Because multiple forecasts are issued
Table 9: Assessing Risk Aversion

<table>
<thead>
<tr>
<th></th>
<th>(1) Catch</th>
<th>(2) Catch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.024</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.070</td>
<td>-0.32***</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Skill</td>
<td>-0.20***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td></td>
</tr>
<tr>
<td>Skill × Niño 3.4</td>
<td>-0.28***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td></td>
</tr>
<tr>
<td>Ensemble sq. error</td>
<td></td>
<td>-0.17***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.028)</td>
</tr>
<tr>
<td>Ensemble sq. error ×</td>
<td></td>
<td>0.080***</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td></td>
<td>(0.016)</td>
</tr>
<tr>
<td>Baseline controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>152,327</td>
<td>158,371</td>
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</tbody>
</table>

Notes: The table shows results from estimating equation (10) on monthly data. The dependent variable in each model is standardized total catch per month. In addition to the listed variables, all models contain vessel, year, and month-of-year fixed effects as well as two additional lags of realizations and forecasts of the Niño 3.4 index. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

beginning in the 1990s, the standard deviation of the plume gives a summary measure of disagreement across the different forecasters. This measure is model-dependent and influenced by model errors, so it does not necessarily represent the full probability distribution of a single forecast, but it plausibly affects the confidence that harvesters have in the projections. One should expect that a risk-averse agent will adapt less if this standard deviation measure is higher. Indeed, Table 9 Column 2 shows that if the forecast plume is wider, adaptation falls. The results also show that agents are responding to forecast-specific characteristics, lending support to the assumption that agents are directly consuming these predictions rather than reacting to something else that is correlated with forecasts but not ex ante information.
7.2 Learning about ENSO and forecasts

By using a single public forecast to measure adaptation, the results assume that all individuals have the same beliefs about ENSO. Differences in ability to understand forecasts, heterogeneity in risk tolerance, or access to private information could alter the conclusions.\(^{36}\)

### Table 10: Experience with ENSO Events

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ENSO</td>
<td>El Niño</td>
<td>La Niña</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.098***</td>
<td>-0.064**</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.028)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.23***</td>
<td>-0.26***</td>
<td>-0.21***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.034)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Niño 3.4 × Experience</td>
<td>0.013***</td>
<td>0.020***</td>
<td>0.026***</td>
</tr>
<tr>
<td></td>
<td>(0.0029)</td>
<td>(0.0063)</td>
<td>(0.0051)</td>
</tr>
<tr>
<td>Niño 3.4 × Experience</td>
<td>-0.011***</td>
<td>-0.013*</td>
<td>-0.026***</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td>(0.0069)</td>
<td>(0.0053)</td>
</tr>
<tr>
<td>(B_n(A)) low experience</td>
<td>0.78***</td>
<td>0.86***</td>
<td>0.74***</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.073)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>(B_n(A)) medium experience</td>
<td>0.90***</td>
<td>0.92***</td>
<td>0.89***</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.072)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>(B_n(A)) high experience</td>
<td>1.02***</td>
<td>0.99***</td>
<td>1.05***</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.076)</td>
<td>(0.080)</td>
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<tr>
<td>Baseline controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Experience trend</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>159,602</td>
<td>159,602</td>
<td>159,602</td>
</tr>
</tbody>
</table>

**Notes:** The table shows results from estimating a modified version of equation (9) on monthly data. The dependent variable in each model is standardized total catch per month. In addition to the listed variables, all models contain vessel, year, and month-of-year fixed effects as well as two additional lags of realizations and forecasts of the Niño 3.4 index. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Here, I focus on heterogeneity in experience with ENSO. A captain or vessel owner with more experience fishing during ENSO conditions might be better equipped to

\(^{36}\)See, for instance, Kala (2015) for recent evidence on behavioral responses to weather risk.
handle the adverse climate, increasing adaptation. If the forecasts turned out to be unhelpful, a more experienced captain might engage in more *ex post* adaptation, lowering the effect of forecasts.

Table 10 investigates this hypothesis by including vessel-specific trends that increment each time a vessel experiences any ENSO event (Column 1), just an El Niño event (Column 2), or just a La Niña event (Column 3). Overall, the results suggest that there is an important learning effect. Vessels that have been through more ENSO events adapt at a higher rate. This relationship is summarized in the middle section of the table which shows the normalized benefit of adaptation for novice, experienced, and highly experienced vessels.\(^{37}\) For a novice vessel (both 25\(^{th}\) percentile experience), adaptation is about 20% lower than for a very experienced vessel (75\(^{th}\) percentile experience).

8 Conclusion

Environmental impacts from a variety of source are currently large and, for many important cases, are not being address by collective action at a scale appropriate to the potential damages. If public policy is not appropriately aggressive, then individual and firm adaptation will need to play an outsize role damage reduction. Adaptation does not occur in a vacuum, however. Individuals 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 affecting forward-looking adaptation. The effect of information on adaptation also 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 firms with flexible production, this paper assesses the degree of forward-looking adaptation using an estimating equation informed by a structural model of adaptation to a stochastic weather process. Detailed panel data and a unique set of real-time historical ENSO forecasts allow for estimation of the role of information in climate adaptation, showing that anticipation of ENSO allows harvesters to take action that substantially reduces the direct effects this climate variable.

From a methodological standpoint, the empirical strategy presented here has the potential to be applied to many settings. The novel collection of ENSO forecasts assembled for the project and the estimation strategy should allow for investigation of adaptation to ENSO processes in a number of different settings. Public forecasts

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\(^{37}\)The experience trends are defined at the vessel level because captain identities are not consistently reported in the logbook records.
of other weather, climate, and pollution processes can similarly be harnessed to understand expectation-driven behavior.

Whether these estimates should influence broader discussions of optimal climate change mitigation policy hinges on extrapolating the results dynamically and across other firms. The magnitude of the change in temperature caused by ENSO—2 to 4°C for a complete El Niño to La Niña cycle—is comparable to the average warming currently being forecast for the coming century (IPCC, 2014). Perhaps the more important difference when extrapolating the effects of ENSO to the effects from global climate change is that ENSO-driven changes are temporary, rarely lasting for more than two years. Therefore, attention to dynamics is critical to understanding whether the estimates presented in this paper have bearing on the effects of long-run climate change.

At least three arguments suggest that short-run adaptation estimates provide lower bounds for long-run adaptation. First, if an adaptation mechanism is inexhaustible and it is available in the short run, then it will be available in the long run. Second, if a firm owner expects a change in the environment to be permanent, then he or she will be more willing to take adaptive actions that require long-term investments. Third, technical change might improve the adaptive capacity of a given production process.

On the other hand, if adaptation mechanisms are exhausted, if agents hit corner solutions, if the prices of adaptation mechanisms rise too rapidly, or if climate change causes more extreme weather impacts, then short-run adaptation estimates will not be as good of a guide for the long run. Moreover, as Hornbeck and Keskin (2014) shows empirically, long-run 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 climate-exposed long-run position. In the setting of this paper, one important adaptation mechanism—timing entry and exit from the fishery—cannot be indefinitely maintained. If climate change permanently pushes fishing grounds so far offshore that entry is never profitable in expectation, then this adaptation will no longer provide any aid. The question of dynamics in individual adaptation to a changing climate is an important open questions in climate economics.

These results are encouraging for the prospects of adaptation by other highly mobile firms with ready access to non-climate exposed production processes. The results also inform the potential effectiveness of information as a climate adaptation policy. According to the baseline results, forecast provision has been 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. Information externalities imply that public provision of forecasts of weather and climate changes can have a positive welfare impact even if adaptation mechanisms themselves are private.

References


Appendix for online publication
A Model extensions

A.1 Non-separable weather

The model in Section 2 assumed that weather and inputs were multiplicatively separable. Without assuming this separability, the definition of adaptation and estimation strategy still hold, but the relatively simple dependence of adaptation on a single function of weather will no longer hold.

Consider a single input model but without the separability assumption. Formally, let the firm solve

\[
\max_x \mathbb{E}_{t-1}[\pi_{it}] = p_{1t}\mathbb{E}_{t-1}[f(x_{it}, Z_{it})] - p_{2t}x_{it}.
\]

(11)

Suppressing entity and time subscripts and using subscripts on equations to denote partial derivatives, the first order condition will be

\[
p_1\mathbb{E}[f_1(x, Z)] - p_2 = 0
\]

(12)

By the implicit function theorem, one can find

\[
\frac{\partial x}{\partial \mathbb{E}[Z]} = -\frac{\partial \mathbb{E}[f_1(x, Z)]}{\partial \mathbb{E}[Z]} \left(\frac{\partial \mathbb{E}[f_1(x, Z)]}{\partial x}\right)^{\frac{1}{2}} = -\frac{\partial \mathbb{E}[f_1(x, Z)]}{\partial \mathbb{E}[Z]} \mathbb{E}[f_{11}(x, Z)]^2.
\]

(13)

Similar expressions can be derived for other moments of the weather distribution, suggesting that a semiparametric procedure for estimating this more general model would be to include progressively higher moments of the weather forecast distribution in the estimating equation. Such a procedure would require a rich forecast (of the probability density, for instance) or a simple weather process. Formal identification of this model comes from application of recent results in identification of nonparametric instrumental variables models with non-separable error.

Let the optimal input choice be

\[
x^*_{it} = \arg\max_x \{p_{1t}\mathbb{E}[f(x_{it}, Z_{it})]\hat{z}_{i[t-1]} - p_{2t}x_{it}\},
\]

(14)

where \(\hat{z}_{i[t-1]}\) is the vector of forecasts of moments of the distribution of \(Z_t\) that the agent forms based on the information set \(\mathcal{G}_{t-1}\).\(^{38}\) This problem yields an optimal choice for \(x\) denoted \(x^*_t = h(\hat{z}_{i[t-1]}, \eta_t)\) where \(\eta\) contains everything that shifts factor

\(^{38}\)Under loss functions discussed in Section A.4, this vector is simply the conditional expectation of \(Z_t\).
demand other than expectations about the weather. Finally, denote deviations from
expected weather by $\varepsilon_{n,t} = \mathbb{E}[Z^*_n] - \hat{z}_{n,t|t-1}$, where $n$ indexes the moments of
the weather distribution, and collect these deviations in the vector $\varepsilon_t$.

Assuming that $x_t$ is strictly monotonic in $\eta_t$ and that $\hat{z}_{t|t-1}$ is independent of $\eta_t$
and $\varepsilon_t$, the results from Imbens and Newey (2009) can be applied to identify $f$. Two
of these assumptions are natural in this setting. In the model, $\eta$ contains prices, so
the law of demand gives monotonicity. A sophisticated forecaster will ensure that $\hat{z}$
is exogenous with respect to $\varepsilon_t$. Finally, a maintained assumption is that prices are
independent of expected weather, leading to independence of $\eta$ and $\hat{z}$.

This more general identification reinforces the intuition from the separable case
presented in the body of the paper. Forecasts errors are useful for identifying direct
effects of weather, and under the assumption that forecasts only affect inputs, the
factor demand can be fully recovered even if prices are not observed.

A.2 Discrete adaptation

The model presented in Section 2 assumed that all adaptation inputs were continuous
and that the production function was differentiable in all inputs. These assumptions
are not necessary for the formal definition of adaptation, and the estimation strategy
presented in the text extends to the case of discrete adaptations. Continuity and
differentiability simply help to derive exact expressions for the adaptation decision
rule through the implicit function theorem.

In the presence of discrete adaptations, denote adaptation as the vector of changes
in inputs with respect to changes in expected weather, or

$$A = \left( \frac{\Delta x^*_1(p, r, \mathbb{E}[g(Z)])}{\Delta \mathbb{E}[g(Z)]}, \ldots, \frac{\Delta x^*_J(p, r, \mathbb{E}[g(Z)])}{\Delta \mathbb{E}[g(Z)]} \right)'.$$

In this case, estimation proceeds as in Section 4. For a single input, estimating
adaptation can be thought of as estimating the reduced form of an instrumental
variables (IV) regression where the first stage is a regression of weather expectations
on inputs and the second stage is a regression of inputs on output conditional on
realized weather. In this case, the distribution of the input variable is irrelevant to
consistent estimation of the reduced form so long as there is identifying variation in
weather expectations (Wooldridge, 2010, pg. 84).

This result illustrates, however, that the method presented here cannot be used,
in general, to determine the contribution of individual adaptation mechanisms to
total adaptation. In an IV setting, one would need as many instruments as inputs to
fully identify the effect of each input. Expectations only provide a single instrument that is blunt from the perspective of each individual adaptation mechanism. More importantly, because expectations enter all non-separable inputs, omitting one input from the second stage equation would lead to bias.

Finally, a specific example worth highlighting is the case where a firm has the choice of two possible production functions,

$$y_{it} = \begin{cases} f_1(x_{it}) g(Z) & \text{if } \mathbb{E}[f_1(x_{it})] \geq \mathbb{E}[f_2(x_{it})] \\ f_2(x_{it}) g(Z) & \text{if } \mathbb{E}[f_1(x_{it})] < \mathbb{E}[f_2(x_{it})] \end{cases}$$

Define the indicator $d$ as $d = 1 \{ \mathbb{E}[f_1(x_{it})] \geq \mathbb{E}[f_2(x_{it})] \}$ and the probability $p$ as $p = P(\mathbb{E}[f_1(x_{it})] \geq \mathbb{E}[f_2(x_{it})])$, so output can be written as

$$\mathbb{E}[y_{it}] = \mathbb{E}[df_1(x_{it}) g(Z)] + (1-d) \mathbb{E}[f_2(x_{it})] \mathbb{E}[g(Z)].$$

The partial derivative of output with respect to realized weather will be unaffected by this set-up because the weather term can be distributed to the front of the output expression. Moreover, the choice of $x$ is still a function of $\mathbb{E}[g(Z)]$ in both $f_1$ and $f_2$, so the reduced form estimation logic from above applies.

### A.3 Mixed input timing decisions

The model presented in Section 2 assumes that all inputs are decided before the random variable $Z$ is realized each period. Here, I relax that assumption.

Consider two inputs, $x_1$ and $x_2$, where $x_1$ is determined before the random variable realizes (which I will call *ex ante*) and $x_2$ is determined after the random variable realizes (*ex post*). Consider a single firm so that entity subscripts can be dropped and normalize the output price to 1. The problem can be solved by backward induction. The firm’s *ex post* problem is

$$\max_{x_{2t}} \pi_t = f(x_{1t}^*, x_{2t}) g(z_t) - p_1 x_{1t}^* - p_2 x_{2t}$$

given a fixed $x_{1t}^*$ from the beginning of the period and a realization, $z$, of $Z$. The first order condition is

$$f_2(x_{1t}^*, x_{2t}) g(z_t) = p_2$$

This condition makes clear that $x_2$ will generally be a function of the realized weather.
through \( g(z) \). In addition, it will be a function of the expected weather through \( x_1^* \).

For instance, in a Cobb-Douglas case with equal factor shares, the firm would like to equalize inputs \textit{ex ante}, so it would choose \( x_1 \) assuming that \( g(z) = E[g(Z)] \). \textit{Ex post}, the firm still has incentive to equalize inputs, so it will choose \( x_2 \) closer to the \textit{ex ante} value than in a purely \textit{ex post} case.

The \textit{ex ante} value of adaptation given in Equation (4) will be the same, but estimation of this value using realized data will no longer capture all adaptation because

\[
\frac{\partial y}{\partial g(z)} = f_2(x_1^*, x_2^*) \frac{\partial x_2^*}{\partial g(z)} + f(x_1^*, x_2^*).
\]

The second term is the direct effect, as before, but now part of the value of adaptation, \( f_2(x_1^*, x_2^*) \frac{\partial x_2^*}{\partial g(z)} \), will be included in the estimate of the direct effect, which will be included in the magnitude of the coefficient on \( g(z_t) \). This will serve to attenuate the estimate of the value of adaptation and increase the magnitude of the estimate of the direct effect. Therefore, in a case with both \textit{ex ante} and \textit{ex post} adaptation, the effect of forecasts on revenue bounds total adaptation from below, and the effect of realizations conditional on forecasts bounds the direct effect from above.

### A.4 Forecast sufficiency under unbiasedness

In Section 4, simple conditions were given for when forecasts will be perfect proxies for private beliefs. Here, I consider alternative assumptions about the information sets of private agents and a public forecaster and derive implications for the use of forecasts as expectation proxies under the assumption of unbiased forecasts. This setting also allows consideration of forecast dynamics.

To simplify the analysis, consider a weather loss function based on the profit maximization problem given in Equation (1). The function describes the profit or output loss that results from realizations of the random variable \( Z \). Denote expected loss as

\[
E[L^p(Z_t, \hat{Z}_t, X(\hat{Z}_t), p_t)|\mathcal{G}_{t-h}]
\]  

(16)

where we now allow inputs to be a vector and expectations about the future weather are denoted by \( \hat{Z} \). \( \mathcal{G}_t \in \mathcal{F} \) is the information available to the firm at time \( t \), so this function gives losses due to the \( h \) period ahead (or \( h \) horizon) forecast. Denote the argument that minimizes Equation (16) in terms of \( \hat{Z}_t \) by \( s^p_{t|t-h} \), where the superscript \( p \) denotes that this is the private firm's value.
Assume that the firm’s loss function is symmetric about \( Z_t = 0 \). Call the loss function a *Granger loss function* if either of the two following conditions hold

1. The first derivative of the function, \( L^p \), is strictly monotonically increasing over the range of \( Z_t \) and \( \bar{f}(Z) \) is symmetric about \( Z = s^p \) where \( \bar{f}(Z) \) is the conditional distribution of \( Z_t - \mathbb{E}[Z_t|\mathcal{F}_{t-h}] \).

2. The distribution of \( Z, f(Z) \), is symmetric about \( Z = s^p \), is continuous, and is unimodal.

Under either of these conditions, it can be shown that the optimal forecast is \( s_{t|h}^p = \mathbb{E}[z_t|\mathcal{F}_{t-h}] \) (Granger, 1969). Symmetric loss is limiting but allows for greatly simplified analysis and easier nonparametric identification. The other conditions are more benign. Condition 1 says that there can be no flat regions in the loss function and that the unforecastable component of the stochastic process is elliptical. With positive marginal cost of action or a quadratic loss function, condition 1 will be met. Condition 2 is met by any elliptical distribution.

Now, consider a professional forecaster that minimizes mean squared error (MSE) conditional on the information set \( \mathcal{F}_{t-h} \)

\[
\begin{align*}
  s_{t|h} &= \arg\min_{\hat{s}} \mathbb{E}[(z_t - \hat{s})^2 | \mathcal{F}_{t-h}].
\end{align*}
\]

Solving the minimization problem, one finds that the public forecast in this case is

\[
  s_{t|h} = \mathbb{E}[z_t | \mathcal{F}_{t-h}].
\]

Minimization of MSE loss is used in practice by many weather forecasting agencies (Katz and Murphy, 1997).

*Patton and Timmermann* (2012) show that MSE forecasts have the following properties which will be useful below.

1. Forecasts are unbiased for all \( h \)
2. Forecast errors are unpredictable: \( \mathbb{Cov}(s_{t+h|t}, x_t) = 0 \) for all \( x_t \in \mathcal{F}_t \)
3. Longer lead forecasts are less precise:
   - \( \mathbb{V}(s_{t+h|t}) \leq \mathbb{V}(s_{t+H|t}) \) for all \( h \leq H \)
   - \( \mathbb{V}(\varepsilon_{t+h|t}) \leq \mathbb{V}(\varepsilon_{t+H|t}) \) for all \( h \leq H \) where \( \varepsilon_{t+h|t} = z_{t+h} - s_{t+h|t} \) is the forecast error
We also need to be able to compare private forecasts to public forecasts. The lemma below says that variance of forecast error is sufficient for comparing forecast quality.

**Lemma A.1.** If \( G_t \supseteq F_t \) and \((F_t)_{t \geq 0}\) is strictly monotonic, then there exists a forecast \( s_{t|t+k} \) such that \( \nabla (\varepsilon_{t|t+k}) = \nabla (\varepsilon_{p_{t|t}}) \) for \( k \geq 0 \).

**Proof.** Forecast properties gives us that \( \nabla (\varepsilon_{t|t}) \geq \nabla (\varepsilon_{p_{t|t}}) \geq \nabla (\varepsilon_{t|t}) \).

Therefore, by continuity there must exist a \( k \geq 0 \) satisfying the condition. \( \square \)

**Lemma A.2.** For two forecasts \( s_{t+h|t}^1 \) and \( s_{t+h|t}^2 \), an agent with a Granger loss function will choose the forecast with lower variance.

**Proof.** For condition one, this result holds due to increasing loss for larger deviations in \( Z \). For condition two, the higher variance forecast will create a mean-preserving spread in conditional \( Z \). \( \square \)

We now provide versions of the forecast sufficiency assumption stated in Section 4. Assume that \( G_t \subseteq F_t \). In other words, that the public forecaster has access to more information than the private firm. Then it is intuitive that the public forecasts are strictly better than the private forecast, and the firm should use the public forecasts.

**Proposition A.3.** If the firm loss function or the data generating process satisfies the Granger (1969) conditions and \( G_t \subseteq F_t \), then \( s_{t+h|t}^p = s_{t+h|t} \).

**Proof.** The Granger conditions imply that \( s_{t+h|t}^p = \mathbb{E}[\varepsilon_{t+h|t} | G_t] \), so by Lemma A.1 and MSE-forecast property 3, \( G_t \subseteq F_t \) implies

\[
\nabla (\varepsilon_{t+h|t}^p) \geq \nabla (\varepsilon_{t+h|t})
\]

Therefore by lemma A.2, firm loss is minimized by choosing \( s_{t+h|t}^p = s_{t+h|t} \). \( \square \)

Now consider the case where the private firm knows more than the public forecaster: \( G_t \not\subseteq F_t \).

To estimate adaptation, we are interested in \( \frac{dy}{ds^p} \). If we observed \( s^p \) and \( G_t \supseteq F_t \), the chain rule gives

\[
\frac{dy}{ds^p} = \frac{\partial y}{\partial s^p} + \frac{\partial y}{\partial s} \frac{\partial s}{\partial s^p}.
\]

The question becomes one of how correlated are changes in the two information sets. If the new information enters both \( G \) and \( F \), then \( s \) and \( s^p \) will both change,
and the change in the public forecast will again provide good inference for the change in the private forecast. If, however, $\mathcal{G}$ grows by gaining information that is already possessed by the private agent, then $\frac{\partial s}{\partial s^p}$ will equal 0.

The last case is when $\mathcal{G}_t \not\subseteq \mathcal{F}_t$ and $\mathcal{G}_t \not\supset \mathcal{F}_t$. Here, because forecasts based on $\mathcal{F}_t$ are public, the firm will incorporate the public forecast into their private information, leading to $\tilde{s}^p_{t|\tau} = g(s^p_{t|\tau}, s_{t|\tau})$. For example, if the agent produces an ensemble forecast by weighting each input forecast by the 1 over its variance (denoted by $w = 1/\sigma^2$), the result would be

$$\tilde{s}^p_{t|\tau} = \frac{(w_p s^p_{t|\tau} + w_s_{t|\tau})}{w_p + w}$$

$$\Rightarrow \frac{\partial \tilde{s}^p}{\partial s} = \frac{w}{w_p + w}$$

In general, the more precise the public forecast relative to the private forecast, the closer the researcher would be to capturing the total effect. If the the public forecasts are not sufficient for the private beliefs of the agent, the ideal estimation strategy would be to instrument for agent beliefs using the public forecasts.
B Data details and supporting results

B.1 ENSO forecast data

Real-time forecast values are important for identification. I gathered paper records of forecasts issued in by NOAA in the Climate Diagnostics Bulletin (CDB) from June of 1989 until the early 2000s. From the early 2000s to the present, I used and the digital archive maintained by the International Research Institute for Climate and Society (IRI) at Columbia University. The CDB started releasing forecasts in June 1989 and began incorporating the IRI summaries in April 2003.\textsuperscript{39} By the year 2000, the number of forecasts incorporated into the Bulletin had grown from 1 to 8.

Figure A1: Example of ENSO forecast issued in the Climate Diagnostics Bulletin

Notes: The figure shows an ENSO forecast issued in the Climate Diagnostics Bulletin in June of 1989. This figure is typical of the forecasts published between 1989 and 2002. The solid line shows the Niño 3 sea surface temperature anomalies and the X are forecasts (and back-casts). Whiskers are the historical standard error for the forecast, a feature present in this but not all models.

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 the software Graphclick. For Bulletins from 1999 to 2002, I used the online archive of CDBs, again digitizing the figures using Graphclick. For each release, I digitized the Climate

\textsuperscript{39}Throughout, I use the 3-month-ahead forecast for estimation. In the June 1989 release of the CDB, three-month ahead forecasts were released, but NOAA also included estimates of the 1 and 2 month-ahead forecasts in the figure (reproduced below as Figure A1). The June 1989 CDB forecasts included data through May 1989, so the Bulletin technically includes a 1-month-ahead forecast for June 1989, a 2-month-ahead forecast for July 1989, and a 3-month-ahead forecast for August 1989. New forecasts in subsequent Bulletins were at the 3-month-ahead horizon during the initial years of publication.
Prediction Center Canonical Correlation forecast (CPC CCA), the Lamont-Doherty Earth Observatory (LDEO) forecasts version 1, 2, and 3; the National Center for Environmental Prediction (NCEP) forecasts, and the Linear Inverse Model (LIM) forecasts. Other forecasts were either issued as maps or contained idiosyncratic issues that prevented digitization.

For data from 2002 through 2016, I used IRI data helpfully supplied to me by Anthony Barnston. These IRI data have formed the basis for analyses of ENSO forecast performance in Barnston et al. (2010, 2012).

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 CPC CCA forecast at a 3 month horizon, 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 a number of reasons. First, all forecasts initially, and many forecasts to the present day, use the Niño 3 index rather than the Niño 3.4 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 Niño 3.4 index. For an alternative method based on scaling alternative index values and visual averaging of maps, see the IRI ENSO Quick Look.

B.2 Albacore prices

Albacore prices come from the PacFIN database and are available from 1981 to 2016 at the annual level for ports in the continental United States. Prices are matched to catch using the landing port reported by the vessel.

B.3 Fuel prices

Monthly port-level fuel prices are available for ports in Washington, California, and Oregon from 1999 to the present. The prices are gathered using a phone survey during the first two weeks of each month. The survey respondents are asked to give the price per gallon or price per 600 gallons for number 2 marine diesel before tax.

From 1983 to until the end of 1993, state level prices for number 2 distillate are used for Washington, Alaska, and Oregon. From 1994 until the end of 1998, highway grade number 2 diesel price is used. For Alaska, the state average diesel price is also used for the 1999 to 2016 period.
For California, the distillate price series is not available. State average diesel price is used starting in July of 1995. Prior to July 1995, the gasoline price is used, after accounting for seasonality. In particular, using all data where I observe both gasoline and diesel prices (1994 through 2016) I run the regression

$$diesel_t = \alpha_{\text{month}} + \gamma_0gas_t + \gamma_{\text{month}}gas_t + \varepsilon_t$$

where $diesel$ is the diesel price, $gas$ is the gasoline price, $\alpha_{\text{month}}$ is a fixed effect for each month of the year ($1, \ldots, 12$), and $\gamma_{\text{month}}gas_t$ is an interaction between a fixed effect for each month and the gasoline price. I then predict the diesel price for the pre-1994/5 period using the coefficients from this regression and the observed gasoline price from 1983 to 1995. This procedure should account for intra-year changes in the diesel-gasoline price gap caused by seasonal demand for heating oil. In practice, the seasonal coefficients are not important for this sample.

The same procedure is used to estimate diesel prices for Hawaii over the full sample.

**B.4 Vessel movement**

Vessel movement is calculated from daily latitude and longitude records plus records of the departure and landing ports. During a fishing trip, movement is calculated as the great circle distance between today's and yesterday’s reported location. Calculations were carried out using the `geodist` package in Stata.

For the date of departure, movement is calculated as the great circle distance between the departure port location and the location reported in the first logbook record for the trip. For the final day of the trip, movement is calculated as the great circle distance between the last location reported in the logbook and the landing port.

**B.5 Catch weight**

Exact catch weight was not recorded in the logbook records for roughly one-third of the daily observations. For the missing records, weight was interpolated in order to obtain complete records for the creation of revenue measures. The interpolation used two methods. First, if a total weight of fish catch was recorded for the trip, then this average weight was used for all fish caught on the trip. For the remaining cases, a regression of weight on gear type, year, and month was used to estimate weight.

Table A1 assesses the effect of this interpolation procedure on the baseline results. Column 1 reproduces the baseline results from Table 2 using only the sub-sample of observations with recorded catch weight. Inference is nearly identical to baseline in
Table A1: Robustness to Interpolation of Catch Weight

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Catch</td>
<td>Catch weight</td>
<td>Catch weight interpolated</td>
<td>Revenue</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.036</td>
<td>-0.043*</td>
<td>-0.028</td>
<td>-0.089***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.27***</td>
<td>-0.27***</td>
<td>-0.28***</td>
<td>-0.15***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.032)</td>
</tr>
</tbody>
</table>

Covariates: Baseline Baseline Baseline Baseline
Weight measure: Observed Observed Interpolated Observed
Observations: 157,394 157,394 159,602 129,314

Notes: The table shows results from estimating versions of equation (9) on monthly data. The dependent variable in each model is monthly number of fish caught. In addition to the listed variables, all models contain vessel, year, and month-of-year fixed effects as well as two additional lags of three-month ahead forecasts and realizations of the Niño 3.4 index unless otherwise noted. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation, unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

this case. Columns 2 and 3 show the baseline regression with catch weight as the dependent variable with and without the interpolation, respectively. One can see that the interpolation increases the magnitude of the results. This occurs because more positive catch observations are being added to the dataset. Finally, Column 4 reproduces the revenue result from the baseline table, again showing slightly larger magnitudes but with similar qualitative results between the interpolated and non-interpolated versions.

B.6 Evidence for Linearity

Figure A2 shows the semiparametric relationship between output and the one-month lag of the Niño 3.4 index in the period before public forecasts existed (from 1981 to June 1989). Both output and the Niño 3.4 index are residualized on baseline controls (year, month-of-year, and vessel fixed effects as well as two additional lags of Niño 3.4). Under the assumption that changes in ENSO relative to the two most recent lags were unforecastable during this period, the plotted relationship recovers the total effect of ENSO on output which, in such a case, would be equal to the direct effect.

From the figure, the relationship between ENSO and output appears to be linear across the range of identifying variation in the Niño 3.4 index. Because this estimate
Figure A2: Semiparametric Relationship Between Output and ENSO Before Public Forecasts Existed

![Graph showing the relationship between catch and Niño 3.4 index](image)

Notes: The figure shows a local linear regression (Epanechnikov kernel with bandwidth of 0.13) of monthly catch on the Niño 3.4 index the previous month. Both variables are residualized on month of year, year, and vessel fixed effects as well as two additional lags of the Niño 3.4 index. The Niño 3.4 index is Winsorized at the 1% level to improve legibility. The sample is from 1981 to May 1989 before ENSO forecasts were released. Shaded area gives the 95% confidence interval.

is plausibly unaffected by omitted variable bias from beliefs, it provides evidence for linearity in the direct effect of ENSO on production in this setting.

B.7 Nonlinear Estimating Equation

Evidence from Figure A2 suggests that a linear specification is reasonable in this setting. *A priori*, however, a nonlinear specification could be reasonable if it is deviations from normal climate in either a hot or cold direction that matter for output. In such a case, a quadratic function for $g$ could approximate the effects of weather.

$$g(z_{t-1}) = \gamma_{q,0} + \gamma_{q,1}z_{t-1} - \gamma_{q,2}z_{t-1}^2$$

(17)

With this function of weather, if agents are forming distributional beliefs about ENSO, then the correct forecast term to include would be $g(\hat{z}_{t-1}) = \gamma_{q,0} + \gamma_{q,1}E_{t-h}[Z_{t-1}] - \gamma_{q,2}E_{t-h}[Z_{t-1}^2]$, where $h$ is how far in advance the forecast was issued (at least $h > 1$)
in this case). In practice, I observe point forecasts of ENSO, so I will use
\[
g(\hat{z}_{t-1}) = \gamma_{q,0} + \gamma_{q,1}\mathbb{E}_{t-h}[Z_{t-1}] - \gamma_{q,2}\mathbb{E}_{t-h}[Z_{t-1}]^2
\]

(18)

This necessitates one of two additional assumptions. Either one can assume that agents are not forming time-varying distributional beliefs about ENSO so that the changes in the point forecast fully capture both linear and nonlinear changes in expectations, or one can assume constant variance of \(Z\). To see the need for the constant variance assumption, assume that agents forecast higher moments of the ENSO distribution. Then
\[
\mathbb{E}[g(Z)] = \gamma_{q,0} + \gamma_{q,1}\mathbb{E}_{t-h}[Z_{t-1}] - \gamma_{q,2}\mathbb{E}_{t-h}[Z_{t-1}^2]
\]

(19)

The difference between this value and the measure used for estimation is
\[
\mathbb{E}[g(Z)] - g(\mathbb{E}[Z]) = \gamma_{q,2}(\mathbb{E}_{t-h}[Z_{t-1}]^2 - \mathbb{E}_{t-h}[Z_{t-1}^2]) = \gamma_{q,2}\mathbb{V}_{t-h}(Z_t)
\]

(20)

If one assumes that \(Z_t\) has constant variance over time, then (20) is constant, and the difference between the two measures will be absorbed by the intercept term. Despite a difference in levels, changes in the two values will carry the same identifying information.

Whether these assumptions limit the interpretation of results is context specific. In Figure A3, I assess the stability of the variance of ENSO over time. Aside from a period of high variance in the late 1990s, ENSO appears to have a stable second moment. Future work would benefit from using distributional forecasts to assess adaptation to changes in the full distribution of weather.

Putting these elements together, the nonlinear estimating equation is
\[
y_{it} = \beta_{q,0} + \beta_{q,1}z_{t-1} + \beta_{q,2}z_{t-1}^2 + \beta_{q,3}\hat{z}_{t-1} + \beta_{q,4}\hat{z}_{t-1}^2 + x_{it}'\alpha_q + \varepsilon_{q,it}
\]

(21)

where \(y_{it}\) is output or revenue for vessel \(i\) at time \(t\), time is measured in months, \(z_{t-1}\) is the realized value of the Niño 3.4 index the previous month, \(\hat{z}_{t-1}\) is the forecast of ENSO, \(x\) is a vector of control variables (vessel, year, and month fixed effects in the baseline specification), and \(\varepsilon\) is a stochastic error term. Adaptation is more complicated to assess with this estimating equation and will be considered formally in Sections B.8 and B.9.
Figure A3: Second Moments

(a) ENSO Rolling St. Dev. and Average  (b) Disagreement in Ensemble Members

Notes: Panel (a) shows the moving average and standard deviation of the Niño 3.4 index. Rolling values use a four year window and monthly data. Panel (b) shows the squared error of ensemble members in the ENSO forecast each month.

B.8 Nonlinear effects of ENSO

Table A2 shows nonlinear effects of ENSO on output and revenue. The left-hand side variable in columns 1 and 2 is output and in columns 3 and 4 it is revenue. Columns 1 and 3 estimate equation (21). Columns 2 and 4 add interactions between the forecast and realization of ENSO. For ease of interpretation, Table A3 shows the marginal effects for each model when both the forecast and realization of ENSO are equal to 1 (moderate El Niño).

The quadratic estimates reinforce the primary results from Table 2. First, in all quadratic models, the squared terms are significantly different from zero, but the models show that over most of the range of the data, the linear model does a reasonable job capturing the effect of ENSO on the fishery.

Second, both forecasts and realizations of ENSO are important for production in this setting. But conditional on forecasts, realizations are generally an order of magnitude less important than the forecasts themselves. In the context of the model, these estimates indicate that the benefit of adaptation is large compared to the direct effect. The marginal effects show this clearly: the marginal effect of the forecast on output is 6 to 10 times larger than the marginal effect of realized ENSO and 2 to 5 times larger for revenue.

Third, models that do not include forecasts show that as in the linear case, excluding forecasts leads to severe bias.\footnote{These results are reported in Tables A5 and A5, with corresponding marginal effects reported} If the forecasts are not included, the direct
Table A2: Effect of ENSO on Standardized Output and Revenue: Quadratic Models

<table>
<thead>
<tr>
<th></th>
<th>(1) Catch</th>
<th>(2) Catch</th>
<th>(3) Revenue</th>
<th>(4) Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.016</td>
<td>-0.031</td>
<td>-0.084***</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.027)</td>
<td>(0.021)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>-0.026**</td>
<td>-0.085***</td>
<td>-0.017*</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.023)</td>
<td>(0.0094)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.24***</td>
<td>-0.26***</td>
<td>-0.14***</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>-0.085***</td>
<td>-0.17***</td>
<td>-0.075***</td>
<td>-0.23***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.027)</td>
<td>(0.018)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td></td>
<td></td>
<td>0.16***</td>
<td>0.26***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.048)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Baseline controls Yes Yes Yes Yes
Unique Vessels 1,224 1,224 1,214 1,214
Observations 159,602 159,602 131,296 131,296

Notes: The table shows results from estimating equation (21) on monthly data. The dependent variable in each model is indicated at the top of the column. All dependent variables are standardized. Catch is the total number of fish caught per month. Revenue is the total ex-vessel value of catch. Additional controls are the same as in Table 2 and are two additional lags of the Niño 3.4 index, two additional lags of forecasts, and fixed effects for vessel, year, and month. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

effect of a moderate El Niño is over-estimated by roughly 100% while the total effect is under-estimated by about 100% as well.

The normalized benefit of adaptation in these models depends on realizations of ENSO and the relevant forecast. Section B.9 discusses this measure in detail, but the basic intuition can be captured by comparing the marginal effect of forecasts to the sum of the marginal effect of forecasts and realizations. This value is the normalized marginal benefit of adaptation when a moderate El Niño hits. For output, the ratio is 0.86 for the quadratic specification in column 1 and 0.92 for the quadratic specification with interactions in column 2. The comparable measures for revenue are 0.71 and in Tables A6 and A8.
Table A3: Marginal Effects of Quadratic Models at Niño 3.4 and Niño 3.4 Equal to 1

<table>
<thead>
<tr>
<th>Model</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Catch</td>
<td>Catch</td>
<td>Revenue</td>
<td>Revenue</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.067</td>
<td>-0.039</td>
<td>-0.12***</td>
<td>-0.070***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.037)</td>
<td>(0.029)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.41***</td>
<td>-0.43***</td>
<td>-0.29***</td>
<td>-0.33***</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.050)</td>
<td>(0.043)</td>
<td>(0.047)</td>
</tr>
</tbody>
</table>

Notes: The table shows marginal effects from estimates in Table A2. Standard errors calculated using the delta method. Significance indicated by: *** p < 0.01, ** p < 0.05, * p < 0.1.

0.83. In all cases, adaptation is a large fraction of the total effect of ENSO. The more complete analysis in Section B.9 reinforces this point, showing that normalized adaptation is high—greater than 50% for all methods of calculating the measure and near 100% in all cases for output.

Finally, the non-zero interaction terms allow for more complex results when forecasts and realizations differ. If the realization of ENSO is 1 and the forecast is unexpectedly high, the direct effect is attenuated and can even turn positive for sufficiently benign conditions. In contrast, if the firm expects conditions to be more benign than an ENSO of 1, then the direct effect is substantially worse. Similar results hold when considering a fixed forecast and changes in realizations of ENSO.

B.9 Univariate measure of adaptation value for quadratic specifications

Comparing the value of adaptation with the residual, direct effect helps to determine whether the magnitude of total adaptation is large and aids in comparisons with other studies. In particular, the value of adaptation can be normalized by dividing by the total derivative of output with respect to a change in climate,

$$B_n(\mathbf{A}) = \frac{B(\mathbf{A})}{dE_{t-1}^{g_t}/dE_{t-1}^{g(Z_t)}}.$$  

(22)

The normalization creates an intuitive adaptation index because the total change in output with respect to a change in climate can be decomposed into the change due
to adaptation and the change due to direct effects.

\[
\frac{dE_{t-1}[y_t^*]}{dE_{t-1}[g(Z_t)]} = \frac{\partial E_{t-1}[y_t^*]}{\partial x_t^*} \cdot \frac{\partial x_t^*}{\partial E_{t-1}[g(Z_t)]} + \frac{\partial E_{t-1}[y_t^*]}{\partial E_{t-1}[g(Z_t)]}
\]  

(23)

If the value of adaptation is high relative to the direct effect, then this value will be close to one. If adaptation is zero, this term will be equal to zero. The normalized benefit of adaptation also has a welfare interpretation under the assumption of continuous inputs. Given a choice over two continuous production technologies with the same costs, a firm would rather choose the technology with lower \( \frac{\partial E_{t-1}[y_t^*]}{\partial E_{t-1}[g(Z_t)]} \) relative to \( \frac{\partial E_{t-1}[y_t^*]}{\partial x_t^*} \cdot \frac{\partial x_t^*}{\partial E_{t-1}[g(Z_t)]} \), because the second term will be zero according to the first order condition and is therefore profit neutral, while the direct effect influences profit. Therefore, the firm would prefer the technology with a higher normalized benefit of adaptation, all else equal.

Estimating the normalized benefit of adaptation is straightforward if the effect of climate on revenue (and profit) is linear. In nonlinear specifications discussed in Section B.7, the calculation poses a problem, however, because the derivative of \( g \) will be zero at the peak of the quadratic curve. This will cause the mean of the total effect to be zero at this point, leading to division by zero. Figure A2 and the estimates from Table 2 show that the peak of the quadratic occurs near the center of the ENSO distribution, so this issue is a problem in practice.

Table A4: Normalized benefit of adaptation, quadratic models

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Catch</td>
<td>Catch</td>
<td>Revenue</td>
<td>Revenue</td>
</tr>
<tr>
<td></td>
<td>Quadratic</td>
<td>Interaction</td>
<td>Quadratic</td>
<td>Interaction</td>
</tr>
<tr>
<td>Estimator of ( B_n(A) )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0.93</td>
<td>0.93</td>
<td>0.66</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>[0.88,0.98]</td>
<td>[0.88,0.98]</td>
<td>[0.61,0.71]</td>
<td>[0.61,0.70]</td>
</tr>
<tr>
<td>Conditional average</td>
<td>0.85</td>
<td>0.97</td>
<td>0.48</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>[0.34,1.56]</td>
<td>[0.85,1.10]</td>
<td>[0.14,1.04]</td>
<td>[-0.37,1.50]</td>
</tr>
<tr>
<td>Limit as Niño 3.4 → ∞</td>
<td>0.77</td>
<td>0.95</td>
<td>0.81</td>
<td>1.26</td>
</tr>
<tr>
<td></td>
<td>[0.57,0.96]</td>
<td>[0.75,1.16]</td>
<td>[0.63,1.00]</td>
<td>[0.95,1.57]</td>
</tr>
</tbody>
</table>

Notes: The table shows results from three estimators of Equation (22) using monthly data and quadratic specifications. The dependent variable in each column corresponds to a model from Table A2. 95% confidence intervals are shown in parentheses and are calculated by the delta method for the limit and by bootstrap in the case of the conditional mean and the median.
There are a number of possible solutions to the division-by-zero problem, and in this section, I pursue three of them to compare their effect on the estimated, normalized benefit of adaptation. First, for the parametric specification used in the baseline results, one can take a limit of the numerator and denominator of Equation (22) as Niño 3.4 goes to infinity. In the quadratic specification without interactions, this limit is not a function of ENSO, and $B_n(A)$ simplifies to be $\beta_4 / (\beta_2 + \beta_4)$, where the coefficients are those from Equation (21). This method has the advantage that standard errors can be easily calculated using the delta method under the assumption that $\beta_4 \neq 0$. When including interactions between Niño 3.4 and the forecast, the limit becomes

$$B_n(A) = \frac{2\beta_4 + \beta_5}{2\beta_2 + 2\beta_4 + 2\beta_5},$$

where $\beta_5$ is the coefficient on the interaction between Niño 3.4 and the forecast.

Second, one can calculate the median of $B_n(A)$ using the empirical distribution of ENSO. The median is less subject to outliers caused by division by zero. For both the conditional mean and the median, standard errors are calculated by bootstrap over the parameter estimates from Table 2 and the empirical distribution of ENSO given by Niño 3.4 values from 1989 to 2010. Results using 3,000 bootstrap replications are shown.

Third, one can condition on being away from the point of zero slope when estimating the expectations in Equation (22). This method is convenient, but it also has a nice interpretation as capturing adaptation to deviations from conditions to which the firm is well adapted. In the table, I condition on the Niño 3.4 index being greater than 0.5 or less than -0.5 away from the singularity. The results end up being almost identical to the median approach. The 95% confidence interval is again based on 1,000 bootstrap replications.

In all cases, total adaptation is clearly statistically different from 0, in contrast to recent studies of adaptation in other settings (Burke and Emerick, 2016, Dell et al., 2012, Schlenker et al., 2013). In fact, the point estimates are consistently greater than one half. The results show that forward-looking adaptation is substantial in this setting.

Three potential sources of bias also suggest that, if anything, these estimates understate total adaptation. First, if harvesters have private information about ENSO that is not captured by the public forecasts, then the model in Section 2 shows that estimated, forward-looking adaptation will be attenuated. Second, if some adaptation
mechanisms can occur after the effects of ENSO events are known, then forward-looking adaptation is only part of the total adaptation response, and part of the direct effect would actually be an \textit{ex post} adaptive response. I find some evidence for \textit{ex post} adaptation in Section 6, but the small magnitude of the realized ENSO coefficients in Table 2 allows one to infer that there is, at most, only limited adaptation of this type. Third, because the pre-2002 forecasts had to be digitized from printed records, some (likely classical) measurement error probably exists. The ENSO index is consistently well measured over the estimation sample period since it occurs after the advent of satellite and buoy measurement, so the measurement error in the forecasts should lead to attenuation of the forecast coefficient.

C Additional figures and tables

Figure A4: ENSO Cycle

Notes: The ENSO cycle is measured here by the Niño 3.4 index, which is the three month moving average of sea surface temperature anomalies from the Niño 3.4 region of the equatorial Pacific Ocean. 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 ENSO, see Section 3.
Notes: Forecast skill measured by a normalized version of the Brier skill score is indicated by the light gray line. Skill is the exponential of log of 0.5 times squared error of the forecast divided by the squared error of a naïve persistence forecast. The moving average of monthly skill is given by the black line. The moving average is calculated using a local polynomial regression (Epanechnikov kernel with bandwidth of 12 months). The gray, dashed lines indicate different levels of forecast quality. The bottom line is where the professional forecast has twice as high of standard error as a persistence forecast. The middle line is where the two forecasts are of equal quality. The top line is where the professional forecast has half the standard error of the persistence forecast.
Figure A6: Correlation Between Niño 3.4 and Sea Surface Temperature

Notes: The heat map shows correlation between the one month lag of the Niño 3.4 index and sea surface temperature for each quarter degree latitude-longitude grid cell.
Figure A7: Fishing and Transiting Locations for Daily Observations

Notes: The heat map shows correlation between the one month lag of the Niño 3.4 index and sea surface temperature for each quarter degree latitude-longitude grid cell, as in Figure A6. Each point shows a daily observation of either fishing or transiting for a subset of the data from 1981 to 2010.
Table A5: Effect of ENSO on Standardized Output and Revenue

<table>
<thead>
<tr>
<th></th>
<th>(1) Catch</th>
<th>(2) Catch</th>
<th>(3) Revenue</th>
<th>(4) Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.082***</td>
<td>-0.016</td>
<td>-0.10***</td>
<td>-0.084***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.026)</td>
<td>(0.018)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>-0.047***</td>
<td>-0.026**</td>
<td>-0.041***</td>
<td>-0.017*</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.0096)</td>
<td>(0.0094)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td></td>
<td></td>
<td>-0.24***</td>
<td>-0.14***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.034)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td></td>
<td></td>
<td>-0.085***</td>
<td>-0.075***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.026)</td>
<td>(0.018)</td>
</tr>
</tbody>
</table>

| Lagged controls | Yes | Yes | Yes | Yes |
| Vessel FE       | Yes | Yes | Yes | Yes |
| Year FE         | Yes | Yes | Yes | Yes |
| Month FE        | Yes | Yes | Yes | Yes |
| Unique Vessels  | 1,224| 1,224 | 1,214 | 1,214 |
| Observations    | 159,602 | 159,602 | 131,296 | 131,296 |

Notes: The table shows results from estimating equation (21) on monthly data. The dependent variable in each model is indicated at the top of the column. All dependent variables are standardized. Catch is the total number of fish caught per month. Revenue is the total ex-vessel value of catch. Additional controls are indicated at the bottom and are lagged Niño 3.4 index, lagged forecasts (Columns 2 and 4), and fixed effects for vessel, year, and month. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
Table A6: Marginal Effects of Realized and Forecasted ENSO

<table>
<thead>
<tr>
<th>Niño 3.4</th>
<th>(1) Catch</th>
<th>(2) Catch</th>
<th>(3) Revenue</th>
<th>(4) Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>=0.5</td>
<td>-0.13***</td>
<td>-0.041</td>
<td>-0.15***</td>
<td>-0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.033)</td>
<td>(0.024)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>=1</td>
<td>-0.18***</td>
<td>-0.067</td>
<td>-0.19***</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.041)</td>
<td>(0.031)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>=2</td>
<td>-0.27***</td>
<td>-0.12**</td>
<td>-0.27***</td>
<td>-0.15***</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.059)</td>
<td>(0.049)</td>
<td>(0.044)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Niño 3.4</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>=0.5</td>
<td>-0.33***</td>
<td></td>
<td>-0.22***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td></td>
<td>(0.033)</td>
<td></td>
</tr>
<tr>
<td>=1</td>
<td>-0.41***</td>
<td></td>
<td>-0.29***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td></td>
<td>(0.043)</td>
<td></td>
</tr>
<tr>
<td>=2</td>
<td>-0.58***</td>
<td></td>
<td>-0.44***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td></td>
<td>(0.073)</td>
<td></td>
</tr>
</tbody>
</table>

Observations 159,602 159,602 131,296 131,296

Notes: The table shows marginal effects based on the estimates in the corresponding column of Table 2. Standard errors calculated using the delta method. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
Table A7: Effect of ENSO on Standardized Output and Revenue: Quadratic Model with ENSO-Forecast Interaction

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Catch</td>
<td>Catch</td>
<td>Revenue</td>
<td>Revenue</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.082***</td>
<td>-0.031</td>
<td>-0.10***</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.027)</td>
<td>(0.018)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>-0.047***</td>
<td>-0.085***</td>
<td>-0.041***</td>
<td>-0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.023)</td>
<td>(0.0096)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.26***</td>
<td></td>
<td>-0.12***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td></td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>-0.17***</td>
<td></td>
<td>-0.23***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td></td>
<td>(0.025)</td>
<td></td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>0.16***</td>
<td></td>
<td>0.26***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td></td>
<td>(0.048)</td>
<td></td>
</tr>
</tbody>
</table>

Lagged controls  | Yes       | Yes       | Yes       | Yes       |
Vessel FE        | Yes       | Yes       | Yes       | Yes       |
Year FE          | Yes       | Yes       | Yes       | Yes       |
Month FE         | Yes       | Yes       | Yes       | Yes       |
Unique Vessels   | 1,224     | 1,224     | 1,214     | 1,214     |
Observations     | 159,602   | 159,602   | 131,296   | 131,296   |

Notes: The table shows results from estimating equation (21) on monthly data. The dependent variable in each model is indicated at the top of the column. All dependent variables are standardized. Catch is the total number of fish caught per month. Revenue is the total ex-vessel value of catch. Additional controls are indicated at the bottom and are lagged Niño 3.4 index, lagged forecasts (Columns 2 and 4), and fixed effects for vessel, year, and month. In parentheses are spatial-temporal HAC robust standard errors using a uniform kernel, a distance cutoff of 30km, and 2 year lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
Table A8: Marginal Effects of Realized and Forecasted ENSO: Quadratic Model with ENSO-Forecast Interaction

<table>
<thead>
<tr>
<th>Niño 3.4</th>
<th>(1) Catch</th>
<th>(2) Catch</th>
<th>(3) Revenue</th>
<th>(4) Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>=0.5</td>
<td>-0.13***</td>
<td>-0.035</td>
<td>-0.15***</td>
<td>-0.091***</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.031)</td>
<td>(0.024)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>=1</td>
<td>-0.18***</td>
<td>-0.039</td>
<td>-0.19***</td>
<td>-0.070***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.037)</td>
<td>(0.031)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>=2</td>
<td>-0.27***</td>
<td>-0.048</td>
<td>-0.27***</td>
<td>-0.029</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.054)</td>
<td>(0.049)</td>
<td>(0.038)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Niño 3.4</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>=0.5</td>
<td>-0.34***</td>
<td></td>
<td>-0.23***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td></td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>=1</td>
<td>-0.43***</td>
<td></td>
<td>-0.33***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td></td>
<td>(0.047)</td>
<td></td>
</tr>
<tr>
<td>=2</td>
<td>-0.61***</td>
<td></td>
<td>-0.53***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td></td>
<td>(0.077)</td>
<td></td>
</tr>
</tbody>
</table>

Observations 159,602 159,602 131,296 131,296

Notes: The table shows marginal effects based on the estimates in the corresponding column of Table 2. Standard errors calculated using the delta method. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
Table A9: Price Effects of ENSO

<table>
<thead>
<tr>
<th></th>
<th>Albacore price</th>
<th>Fuel price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-4.26</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>(2.67)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>Niño 3.4 × Niño 3.4</td>
<td>0.078</td>
<td>-0.0018</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.0087)</td>
</tr>
<tr>
<td>L.Albacore price</td>
<td>1.12***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>L.Fuel price</td>
<td>0.99***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>36</td>
<td>346</td>
</tr>
</tbody>
</table>

Notes: The table shows results from estimating Newey-West regressions on monthly (fuel prices) or annual (albacore prices) data. The dependent variable in each model is indicated at the top of the column. In parentheses are Newey-West standard errors with 2 lags for autocorrelation. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Robustness Set 1 for Quadratic Specification: Marginal Effects

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vessel by year FEs</td>
<td>Vessel by month FEs</td>
<td>Vessel trends</td>
<td>Niño 3.4</td>
<td>6 lags</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.039</td>
<td>-0.044</td>
<td>-0.039</td>
<td>-0.032</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.030)</td>
<td>(0.037)</td>
<td>(0.036)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.44***</td>
<td>-0.40***</td>
<td>-0.44***</td>
<td>-0.48***</td>
<td>-0.47***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.039)</td>
<td>(0.050)</td>
<td>(0.059)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>Observations</td>
<td>159,463</td>
<td>157,900</td>
<td>159,602</td>
<td>149,967</td>
<td>154,557</td>
</tr>
</tbody>
</table>

Notes: The table shows marginal effects, evaluated at Niño 3.4 and the forecast of Niño 3.4 equal to 1, from estimating the quadratic version of equation (9) on monthly data. The dependent variable in each model is monthly number of fish caught. All additional covariates, standard errors, and sample are the same as the baseline specification unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
Table A11: Robustness Set 2 for Quadratic Specification: Marginal Effects

<table>
<thead>
<tr>
<th>Year-month clustering</th>
<th>Revenue sample</th>
<th>Less than 46°</th>
<th>Drop 1997 to 2001</th>
<th>Catch lag covariate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.039</td>
<td>-0.066**</td>
<td>0.00053</td>
<td>-0.051*</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.029)</td>
<td>(0.038)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.43***</td>
<td>-0.33***</td>
<td>-0.39***</td>
<td>-0.35***</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.047)</td>
<td>(0.049)</td>
<td>(0.056)</td>
</tr>
</tbody>
</table>

Notes: The table shows marginal effects, evaluated at Niño 3.4 and the forecast of Niño 3.4 equal to 1, from estimating the quadratic version of equation (9) on monthly data. The dependent variable in each model is monthly number of fish caught. All additional covariates, standard errors, and sample are the same as the baseline specification unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Robustness Set 1 for Quadratic Interaction Specification: Marginal Effects

<table>
<thead>
<tr>
<th>Vessel by year FEs</th>
<th>Vessel by month FEs</th>
<th>Vessel trends</th>
<th>Nino 3.4 t − 12</th>
<th>6 lags Nino 3.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.039</td>
<td>-0.044</td>
<td>-0.032</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.030)</td>
<td>(0.037)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.44***</td>
<td>-0.40***</td>
<td>-0.48***</td>
<td>-0.47***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.039)</td>
<td>(0.050)</td>
<td>(0.059)</td>
</tr>
</tbody>
</table>

Notes: The table shows marginal effects, evaluated at Niño 3.4 and the forecast of Niño 3.4 equal to 1, from estimating the quadratic interaction version of equation (9) on monthly data. The dependent variable in each model is monthly number of fish caught. All additional covariates, standard errors, and sample are the same as the baseline specification unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.
Table A13: Robustness Set 2 for Quadratic Interaction Specification: Marginal Effects

<table>
<thead>
<tr>
<th></th>
<th>(1) Year-month clustering</th>
<th>(2) Revenue sample</th>
<th>(3) Less than 46°</th>
<th>(4) Drop 1997 to 2001</th>
<th>(5) Catch lag covariate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño 3.4</td>
<td>-0.039</td>
<td>-0.066***</td>
<td>-0.026</td>
<td>0.00053</td>
<td>-0.051*</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.029)</td>
<td>(0.038)</td>
<td>(0.035)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Niño 3.4</td>
<td>-0.43***</td>
<td>-0.33***</td>
<td>-0.40***</td>
<td>-0.39***</td>
<td>-0.35***</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.047)</td>
<td>(0.049)</td>
<td>(0.056)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Observations</td>
<td>159,602</td>
<td>131,296</td>
<td>157,424</td>
<td>128,546</td>
<td>157,916</td>
</tr>
</tbody>
</table>

Notes: The table shows marginal effects, evaluated at Niño 3.4 and the forecast of Niño 3.4 equal to 1, from estimating the quadratic interaction version of equation (9) on monthly data. The dependent variable in each model is monthly number of fish caught. All additional covariates, standard errors, and sample are the same as the baseline specification unless otherwise noted. Significance indicated by: *** p<0.01, ** p<0.05, * p<0.1.