Climate variability reduces employment in New England fisheries

Kimberly L. Oremus[a,b,1]

[a]School of Marine Science and Policy, University of Delaware, Newark, DE 19716; and [b]Department of Economics, University of Delaware, Newark, DE 19716

Edited by Bonnie J. McCay, Rutgers University, New Brunswick, NJ, and approved November 8, 2019 (received for review November 26, 2018)

Climate change is already affecting fish productivity and distributions worldwide, yet its impact on fishing labor has not been examined. Here I directly link large-scale climate variability with fishery employment by studying the effects of sea-surface pressure changes in the North Atlantic region, whose waters are among the world's fastest warming. I find that climate shocks reduce not only regional catch and revenue in the New England fishing sector, but also ultimately county-level wages and employment among commercial harvesters. Each SD increase from the climatic mean decreases county-level fishing employment by 13%, on average. The South Atlantic region serves as a control due to its different ecological response to climate. Overall, I estimate that climate variability from 1996 to 2017 is responsible for a 16% (95% CI: 10% to 22%) decline in county-level fishing employment in New England, beyond the changes in employment attributable to management or other factors. This quantitative evidence linking climate variability and fishing labor has important implications for management in New England, which employs 20% of US commercial harvesters. Because the results are mediated by the local biology and institutions, they cannot be directly extrapolated to other regions. But they show that climate can impact fishing outcomes in ways unaccounted by management and offer a template for study of this relationship in fisheries around the world.

fishery labor | climate impacts | New England

The world's marine fisheries have been declining for decades, primarily due to overfishing (1). This jeopardizes both the fish stocks' future and the livelihoods of millions who rely on them. Some fishery managers have succeeded in restoring stocks by restricting effort and, more recently, placing quotas on catch (1), but not all fish populations have rebounded as hoped (2). A growing body of literature highlights the effects of climate on fish populations (3) in the context of warming waters (2, 4–6) and interannual variability (7). Models show that failure to account for climate and other forms of uncertainty can exacerbate the pressure stocks face from fishing and ultimately lead to stock collapse (8, 9). This highlights the need for better empirical understanding of climate's impact on fisheries and the communities that depend on them.

Previous studies have extrapolated the results of ecosystem models under climate change to catch and revenue (10, 11) or used idealized management scenarios to project potential economic impacts (12) without empirically examining adaptations or management responses. Yet it is not obvious how fishers, fishery managers, and others in the industry will actually respond. For example, depending on local institutions, a fisher facing diminishing stocks could switch to new species; move to a different region; or exit the industry, among other options. Studies of labor markets in another climate-sensitive natural resource sector, agriculture, show that warming has already led to a range of outcomes, including short-term reallocation, wage rigidity, long-term income loss, and migration (13–15).

In this paper, I empirically measure the impact of climate variability, which includes its observed extremes, on catch, revenue, wages, and employment in the New England fisheries sector. The sector employs an estimated 34,000 commercial harvesters or about 20% of the 166,952 in the United States (16) and a small fraction of the 18.4 million worldwide (1). New England's fisheries are conducive to empirical study of climate's effects because they are among the first to experience rapid ocean warming (2, 17), exhibit strong interannual variability (7), and have a long history of management and data collection (16, 18).

Many studies use temperature anomalies (2) or projections (6) as a proxy for climate change. To avoid omitted variable bias (19), I do not use a local weather variable and instead use a climate index, the North Atlantic Oscillation (NAO), shown in Fig. 1*A* (*SI Appendix*, section 1B). As the dominant regional climate signal in the North Atlantic ocean, NAO influences multiple environmental variables that affect fishing behavior and fish ecology, such as sea-surface temperature (Fig. 1*B*), wind speed, ocean mixing, and their interactions (20–23), systemically modulating ocean productivity (24). NAO has also been identified as a driver of rapid changes in climate (23).

The effects of positive NAO phases and warmer-than-average sea surface temperatures on fish productivity off the coast of New England have been well documented for lobsters, shellfish, and groundfish, especially during the period of spawning through recruitment, when stocks are most vulnerable to physical environmental conditions (2, 6, 7, 25). This body of literature empirically measures how these environmental shocks can lower biomass, landings, or catch for these valuable fisheries. Previous work demonstrates how a positive NAO in the first year

Significance

Beyond their value as a natural resource, marine fisheries employ an estimated 18.4 million commercial harvesters worldwide. Previous research describes how climate change can affect fish populations, but how it will impact fishing employment and communities is not yet understood. New England, which employs 34,000 commercial harvesters, has a well-documented management history and some of the world's fastest-warming waters. This paper provides empirical evidence that fluctuations in a regional climate index reduced county-level fishing employment in New England by an average of 16% between 1996 and 2017. The findings cannot be extrapolated to other regions without further study, but they demonstrate how climate can be linked to fishing employment at a regional level via a biophysical pathway.

Author contributions: K.L.O. designed research, performed research, analyzed data, and wrote the paper.

The author declares no competing interest.

This article is a PNAS Direct Submission.

Data deposition: Data and code for replicating main figures can be found at GitHub, https://github.com/koremus/NAO-NE-fishing-jobs.git.

[1]Email: oremus@udel.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1820154116/-/DCSupplemental.

First published December 9, 2019.

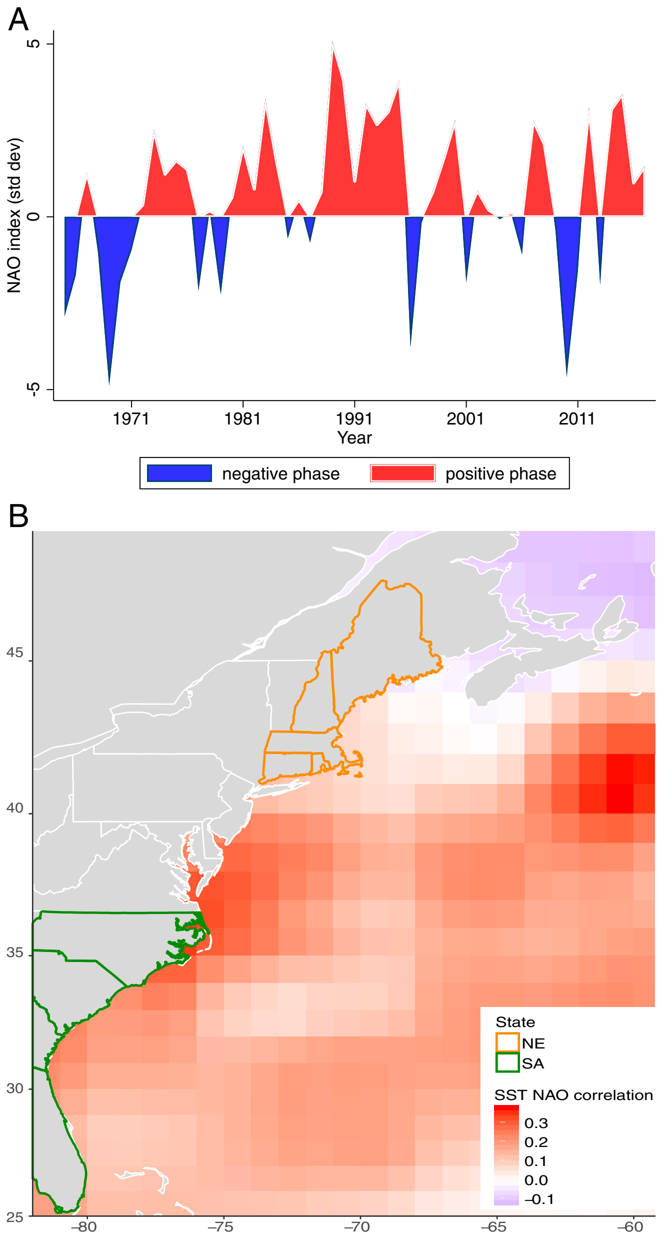

Fig. 1. NAO. (*A*) NAO index. (*B*) NAO and sea-surface temperature. *A* shows the winter (DJFM) NAO index. *B* shows the detrended correlation coefficient between DJFM sea-surface temperature and DJFM NAO index. Positive correlations are red and negative correlations are purple. Study regions include New England in orange and the South Atlantic region in green.

of life persists through the biomass of every age class of New England cod until they are old enough to be caught (7) and shows how lagged NAO events correlate with declines in catch. If natural mortality is greater than managers anticipate or fish productivity is lower than expected, it can lead to quotas that are unintentionally set too high and consequently to overfishing (2). Theoretical models suggest that fishing practices that fail to account for climate impacts on productivity can lead to suboptimal economic harvest, resource rent declines, and even potential collapse (8, 9).

The theoretical pathway from climate shocks to labor outcomes is straightforward. Declines in catch due to NAO are expected to reduce revenue to the extent that fishers are price takers in the fish market and prices are constant. Commercial fishing crews in the eastern United States are often paid in shares (26), so if revenues decline, wages would be expected to decline with them. This could also lead to decreased employment if crews have a reservation wage below which they will not enter fishing in a given year.

Tracking this pathway empirically, however, is complicated by the fact that the intermediary variables (catch and revenue) linking NAO to employment both influence and are influenced by each other, making it hard to identify the direction of causality. For example, if a stock is overfished, management is required to reduce catch until stocks are brought back to sustainable levels. This reduction in catch can lead to a decline in revenue, which can reduce wages and employment. Less labor could lead to less fishing effort, which could increase the fish population, allowing management to increase the total allowable catch (TAC). Notably, the same cycle can theoretically be induced by NAO reducing recruitment, which could deplete stocks and trigger management to reduce catch.

Unlike catch and revenue, NAO is produced independent of the fisheries system, in that NAO may alter fish populations, but changes to fish population, catch, or labor are not expected to alter NAO. This one-way relationship allows for an analysis that links NAO directly to year-to-year variation in each intermediary variable without attempting to disentangle how those intermediary variables interact.

I compare historical NAO data with total county-level fishing wages, employment, and establishments in New England. For example, I compare fishing employment during a positive phase of NAO to fishing employment during a neutral phase, effectively using the same group of fishers as a control for itself. I do this for all NAO events to understand how employment responds to a 1-SD increase or decrease from the climatic mean.

It is also useful to compare all NAO events in New England to those in a control region whose stocks are not systematically impacted by NAO (*Materials and Methods*). Here I exploit the fact that NAO's effect on different fish stocks varies due to ecological differences. In New England, there is evidence that catch of the commercially valuable species is negatively correlated with sea-surface temperatures (SSTs) or NAO (2, 6, 7, 25). In the South Atlantic region, there is a mixture of warm-water and cold-water species. Warm-water species prefer the warmer-than-average winter SSTs associated with a positive NAO phase, whereas cold-water species are adversely affected by these anomalies (27). Shrimp and blue crab account for 53% of commercial revenue in the South Atlantic, and most shrimp stocks in the South Atlantic are warm-water species (27). Most of the groundfish stocks, such as summer flounder, and pelagic stocks, such as bluefish, are cold-water species. Since the employment data (*SI Appendix*, section 1A) mostly reflect individuals employed as fishing crew that can switch between boats and fish stocks throughout the year, it is plausible that they can mitigate shocks in the South Atlantic, but not in New England.

To test whether the South Atlantic is an appropriate control group, I compare catch and revenue in years before and after a 1-unit (1-SD) increase in NAO for the South Atlantic and New England (*Materials and Methods*, *NAO and catch and revenue*). Catch and revenue are aggregated across species for each region, to account for the ability of crew to switch boats and stocks throughout the year. This reduces the number of observations, but enables comparing year-to-year variation in regional fishing revenue with total county-level wages and employment. In addition to examining the relationship between catch and a contemporaneous NAO event, I look at the relationship between catch and past NAO events in the 6 y prior. This is because fish are most vulnerable to their environment from spawning to recruitment (2, 6, 7), making impacts from NAO undetectable in the catch data until they are mature enough to be caught

(7). Finally, I check to see whether year-to-year changes in management are correlated with NAO, to ensure those changes are not confounding the results.

Results

After accounting for secular time trends, the analysis reveals that increases in the NAO signal initially reduce total catch in New England by 2%, but not in the South Atlantic. Fig. 2*A* shows this reduction persists for 5 y. The effect's persistence is expected, given that many stocks have size restrictions on catch that translate to an age at catch (*SI Appendix*, Table S1). For instance, squid and some shrimp are typically caught in their first year of life, most groundfish between age 2 to 4 y, and groupers and some groundfish such as haddock and witch flounder around 4 to 7 y. A majority of fish are caught by age 6 y. Findings are consistent for models with only 1 NAO lag up to 6 NAO lags (*SI Appendix*, Tables S3 and S4), with the magnitude of the effect increasing to a 10% decline in catch as lags are added to the model. This is consistent with previous literature showing the lagged effect of NAO on catch (7). As time progresses from the initial NAO shock, Fig. 2*A* shows a cumulative effect over time as more stocks enter the pool of catch affected by it (*SI Appendix*, section 2).

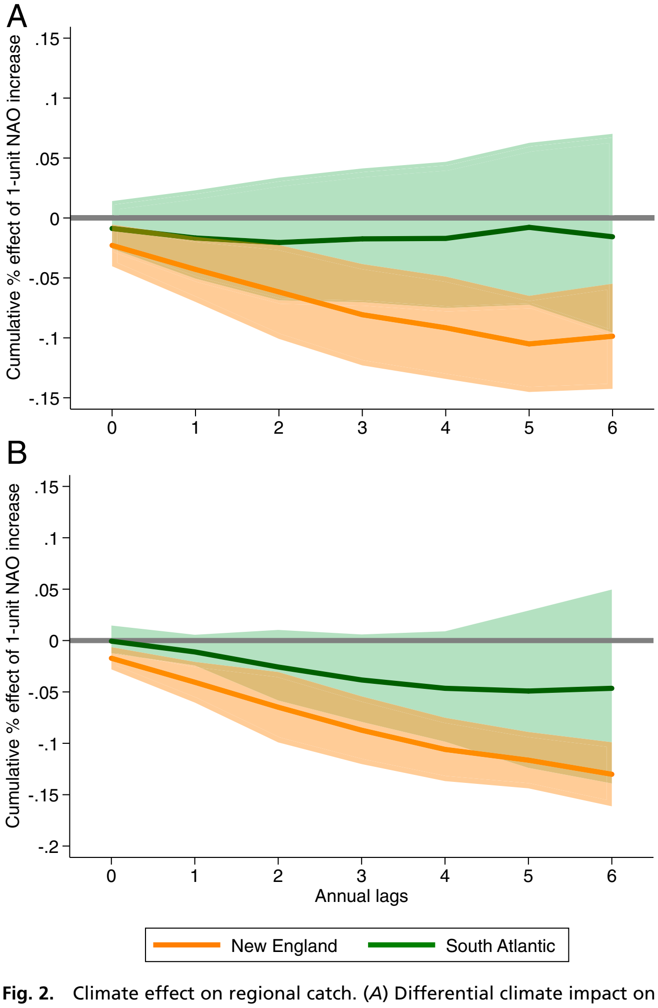

Fig. 2. Climate effect on regional catch. (*A*) Differential climate impact on catch. (*B*) Differential climate impact on revenue. *A* shows the cumulative impact of NAO on regional fish catches, and *B* shows the cumulative impact of NAO on regional fish revenue. Regression coefficients are shown using Eq. **1** with 6 lags of NAO and a fifth-order polynomial time trend. The *x* axis displays the number of years after a 1-unit increase in the NAO index. SEs use the Newey–West adjustment with a bandwidth of 10 y. A 95% confidence interval is shown.

The impact of NAO on regional revenue follows the same pattern as the impact on catch. Fig. 2*B* shows that a 1-unit increase in NAO reduces New England commercial fish revenue by 1% initially, which accumulates to a 13% decline 6 y later. NAO is not significantly correlated with South Atlantic catch and revenue (Fig. 2), even under most alternative lag structures (*SI Appendix*, Tables S4 and S6). This is consistent with literature (27) that finds some warm-water stocks in the South Atlantic benefit from winter SST increases, while others receive negative shocks. This supports the use of a difference-in-difference strategy that compares the effects of NAO on fishing labor in New England, the treated region, to the South Atlantic, the control (*Materials and Methods*, *NAO and fishing labor*).

Over time, the supply shock measurably reduces labor demand. Using a difference-in-difference approach (Eq. **3**), I compare the effects of NAO on wages and employment in the 2 regions. Fig. 3 shows that a 1-unit increase in the NAO index reduces fishing employment by 13% and wages by 35%, effects that persist for several years. Conversely, a 1-SD decrease in NAO increases employment by 13%. Fishing establishments, both employers and nonemployers, follow similar patterns with smaller magnitudes (*SI Appendix*, Tables S9 and S10).

Using a hindcasting model, I hindcast employment with and without NAO (assuming NAO is in a neutral phase for every year) while holding everything else fixed (*SI Appendix*, section 7). Taking the difference between these 2 models, I estimate that NAO is responsible for an on-average 16% decline in county-level fishing employment in New England compared to the South Atlantic, with a 95% confidence interval of 10% to 22%, from 1996 to 2017. This is due to large positive NAO phases in the 1990s (Fig. 1*A*). For comparison, in this time period, average county-level fishing employment declined by about 60% in New England. In other words, the declines attributable to NAO in the average New England county were about 27% of the overall decline.

A series of robustness checks test the model*'s sensitivity to different lag structures (*SI Appendix*, Tables S7–S9), time periods (*SI Appendix*, section 1A), and functional form (*SI Appendix*, section 3 and Fig. S1), such as running the model in levels instead of logs (*SI Appendix*, Table S14). Contemporaneous effects and early lags are sensitive to these specifications, but not later lags, consistent with the impacts on catch.

Many variables beyond climate can impact fishery employment. However, unlike variables such as prices, costs, and management that can simultaneously impact fish populations and be impacted by them, NAO cannot be impacted by fisheries. The analysis captures any changes to these other variables that may be driven by NAO. For instance, if NAO reduces reproduction, this can impact subsequent stock status, triggering management to reduce quotas, which could in turn affect employment.

To control for other potential drivers of employment, the main specification uses year fixed effects to account for any annual factors (such as fuel prices, inflation, and the recession), as well as fishery policies applied to both regions (such as the reauthorization of the Magnuson–Stevens Act in 2006). County fixed effects are used to account for variation in local economies, employment, and fishing practices. The results strengthen with a series of robustness checks. Since the 2 regions are managed by different councils, have different proportions of commercial and recreational fisheries, and comprise different stocks, regional time trends are added, along with an indicator variable to control for adoption of catch-share management (sector programs)

*See *NAO and fishing labor*.

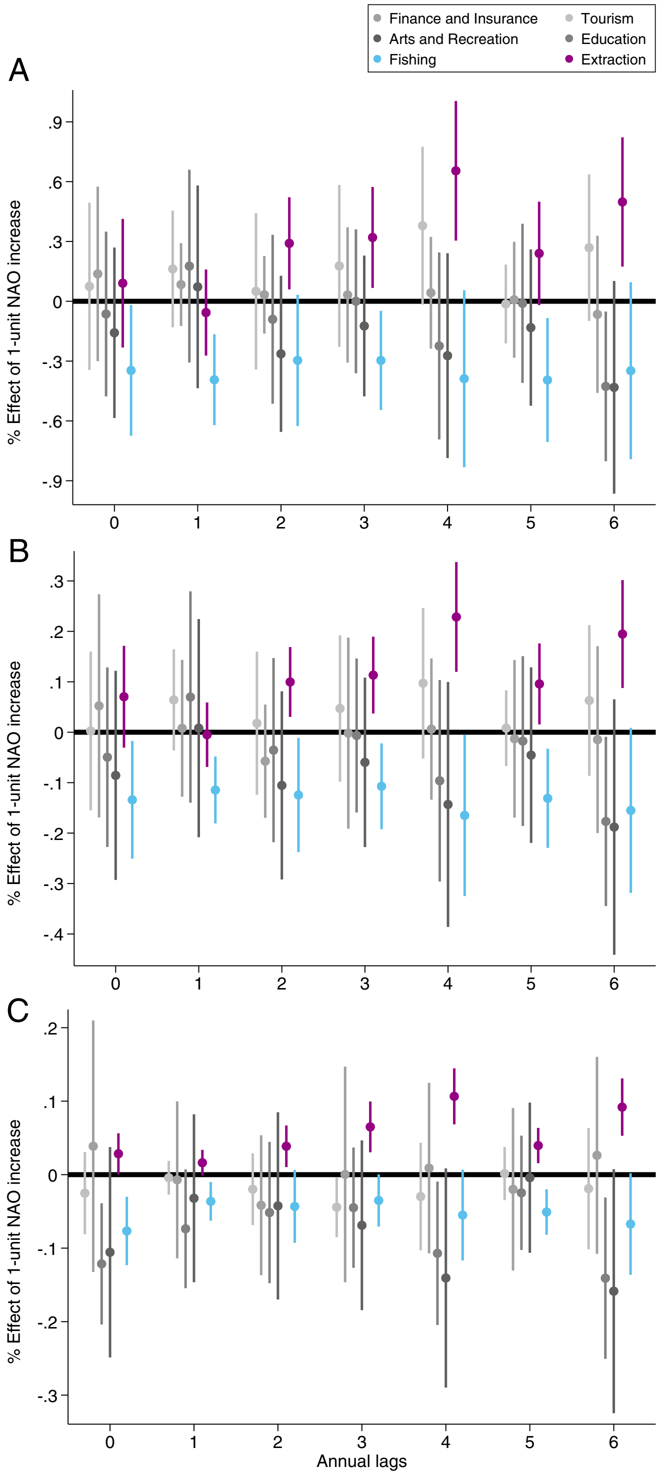

Fig. 3. Climate effect on New England fishing livelihoods and other industries. (*A*) Wages. (*B*) Employment. (*C*) Establishments. Shown is the effect of current and past NAO on (*A*) wages, (*B*) employment, and (*C*) establishments in "treated" New England counties relative to unaffected South Atlantic counties. Regression coefficients are shown using Eq. **3** of employment on lagged NAO events as well as county and year fixed effects. The *x* axis displays the number of years after a 1-unit increase in the NAO index. Commercial fishing is in blue, unaffected industries are in gray, and the extraction industry is in purple. SEs are clustered at the county level. A 95% confidence interval is shown.

in New England, and results remain consistent (*SI Appendix*, Tables S16–S21). To address management confounders that do not change smoothly over time, I test whether lags of NAO are correlated with effort controls, such as annual total allowable catch, restrictions on the number of days at sea, and the number of active lobster traps in New England (*SI Appendix*, section 6). There are few significant correlations between lags of NAO and these management variables (*SI Appendix*, Fig. S3), indicating that management is unlikely to confound the analysis.

To check for unobserved confounders, I run falsification tests. First, I add leads of NAO. Wages and employment do not show any significant correlations to leads of NAO, and the addition of leads does not change the significant effects on lags of NAO (*SI Appendix*, Table S14). Second, the model is run using the same counties that have fishing employment on employment in other industries, such as the finance and insurance, education, arts, and recreational industries and tourism. These industries show no correlation with NAO under different lagged structures (*SI Appendix*, Tables S24–S28).

Discussion

In a managed fishery, it is reasonable to assume that management is a key driver of outcomes such as catch, revenue, and employment. These findings do not contradict that assumption, but they reveal that, at least in New England, climate variation is also affecting these outcomes in a way that is not systematically correlated with changes in management (*SI Appendix*, Fig. S3). Further research should explore why management does not appear to respond to climate variability.

The finding that fishers are leaving fishing in response to NAO events raises the question, Where do they go? The data offer suggestions, but not a definitive answer. Only 2 other sectors have NAO effects with the same lagged structure as fishing: the extraction industry and unemployment. These effects were measured using the same counties that have fishing employment data. Another possibility is that fishers spill over into adjacent regions (28, 29). To guard against this spillover, the analysis omits the Mid-Atlantic region, focusing on 2 regions that are not adjacent to each other. An examination of vessel-permit data (30) for all federal, commercial permits on the Atlantic coast and county labor-force data finds no evidence that fishers from New England are landing in the South Atlantic, moving their boats to the South Atlantic, or leaving New England and moving to the South Atlantic (*SI Appendix*, section 5). Fig. 3 shows a positive correlation between NAO and employment in the extraction industry. The effect matches the declines in employment in the fishing industry in levels (*SI Appendix*, Table S29, column 7). This effect is only in counties with commercial fishing and not on all extraction counties in New England (*SI Appendix*, Table S29, column 8). Finer-resolution data would need to be gathered on a business level to determine whether climate-driven changes in fish productivity are pushing fishers into unemployment, reallocating them into extraction, moving them out of the East Coast, pushing them into retirement, reallocating them randomly into multiple other sectors, or causing some alternative scenario.

NAO shocks spill into fish and seafood markets, decreasing employment by 7% with a 1-y lag, but do not persist (*SI Appendix*, Table S22). There is no impact on fish and seafood wholesalers (*SI Appendix*, Table S23). This implies that these sectors can more readily adjust their supply in response to climate variability. This may be due to access to other markets such as aquaculture, access to catch from other regions, imports, or temporal smoothing.

Unlike fishing permit holders who are restricted to permitted species and may not be able to smooth supply, fishing crews could switch between fisheries. These findings highlight that the portfolio of commercial fish stocks in New England may be mostly impacted by positive NAO events, whereas the portfolio of commercial fish stocks in the South Atlantic is more resilient to these impacts. These findings show that regions' fisheries differ in not only biological resilience to climate change (31), but economic stability as well. Further work on population diversity and edge biomes undergoing range shifts is needed to understand the regional impacts of climate change in different contexts.

The link demonstrated here between climate variability and jobs in the North Atlantic suggests that future analyses of climate's effect on fisheries must consider potential employment impacts and offers one approach for doing so. Whether this relationship applies to other regions of the world will depend on how resilient their ecosystems are to climate variability and how their fishing is managed. Given New England's long history of management, it is possible that livelihood losses might be even greater in less-developed fisheries. Future research in the tropics, especially regions that experience high climate variability such as the tropical Eastern Pacific, may offer further insight into how climate's impacts on fishery productivity and catch translate to livelihood losses in small-scale fisheries. While climate variability has always affected fish and fisheries, anthropogenic climate change raises the stakes for understanding these links and underscores the need to incorporate them into fishery management.

Materials and Methods

Materials.

NAO. The NAO Hurrell winter, December, January, February, and March (DJFM), station-based index measured in SDs from the mean was used from 1965 to 2017 (32). Positive values represent larger pressure differences, which are associated with stronger-than-average westerlies and warmer-than-average sea-surface temperatures off the Atlantic coast of the United States (*SI Appendix*, section 1B).

Catch and revenue. The National Oceanic and Atmospheric Administration's (NOAA) Annual Commercial Landings Statistics (33) were used for landings and revenue by species within the New England and South Atlantic regions for 1971 to 2017. The species in this analysis are summarized in *SI Appendix*, Table S1 and represent 74% of the catch and 75% of the revenue in the South Atlantic and 64% of the catch and 75% of the revenue in New England (*SI Appendix*, section 1D).

Labor. The Bureau of Labor Statistics (BLS) commercial marine fishing wage, employment, and establishment data by year and county area for 1990 to 2017 (NAICS subindustry code 11411) were used, as well as data for fish and seafood markets and wholesalers, nonfishing industries, county-level unemployment, employment, and labor force. Census Bureau data were used for nonemployers in commercial marine fishing (*SI Appendix*, section 1A).

Further data including age at catch by species (*SI Appendix*, section 1E), fishery management (*SI Appendix*, section 6), commercial fishing permits (*SI Appendix*, section 1F), and sea-surface temperature (*SI Appendix*, section 1C) that were used to supplement the analysis can be found in *SI Appendix*.

Methods. There has been a growing literature on climate econometrics (19) that exploits year-to-year variation in weather and climate data to quantify climatic influences on agriculture, income, labor, mortality, crime, and even gross domestic product (34, 35). Following this literature, especially as it pertains to fisheries (7), I use the identifying assumption that NAO is uncorrelated with the error term, such that the year-to-year variation is applying a shock that is developed outside of the fisheries system. This is what allows the analysis to recover a causal signal on catch and fishing labor.

NAO and catch and revenue. First, I estimate the effects of NAO on total regional catch or revenue using a log-linear regression with distributed lags of NAO and flexible polynomial time trends (to account for secular time trends). Due to the well-documented relationship between NAO and biomass (21), I use the specification from Meng et al. (7) of regressing catch on lags of NAO. These lags capture the delayed effects of NAO on catch due to catch-size restrictions:

$$log(landings_t) = \psi + \sum_{\tau=0}^{N} \delta_\tau NAO_{t-\tau} + \sum_{p=1}^{M} \kappa_p t^p + \mu_t. \quad [1]$$

Landings are measured either in total regional metric tons of fish caught and landed at the dock or in dollars of revenue of fish landed (*SI Appendix*, section 1D). ψ is a constant, δ_τ captures the linear effect of NAO τ periods ago, and κ_p represents the effect of a pth-order polynomial time trend. To determine the polynomial order, M, of the time trend, I use the Akaike Information Criterion (AIC). Lower AIC values reflect a model's overall goodness of fit while penalizing additional terms with limited explanatory power. The AIC drops when higher-order polynomials are added but plateaus at a fourth-order polynomial. The AIC is identical for fifth-order polynomials, which is the main specification used in Fig. 2 (*SI Appendix*, Tables S3–S6). The AIC is also used to select the number of lags, N, used in the model. For consistency, a 6-lag specification is used for all of the results, as it has the lowest AIC value for most of the outcome variables, including revenue, wages, and establishments (*SI Appendix*, Tables S5, S8, and S9). This is also consistent with catch size restrictions (*SI Appendix*, Table S1). Furthermore, the addition of a seventh lag does not show significance, but lags 1 to 6 remain consistent with a 6-lag specification (column 7 of *SI Appendix*, Tables S5 and S7–S9). SEs, μ_t, use the Newey–West adjustment, allowing for arbitrary forms of serial correlation and heteroscedasticity in the error term with an optimal bandwidth (36). I also calculate cumulative effects of NAO lags on total catch and revenue (*SI Appendix*, Tables S3–S6).

NAO and fishing labor. This paper uses a difference-in-difference strategy to compare the effect of NAO on fishing labor in New England to its effect on fishing labor in the South Atlantic. I use panel data on fishing wages, employment, and establishments by county and year and define New England counties as treated and South Atlantic counties as untreated. Using a "donut hole" regression (37), I omit the Mid-Atlantic or border region (*SI Appendix*, section 5). Since NAO shocks affect stock recruitment and then propagate to catch over time, I use a log-linear regression with distributed lags to identify the effect of contemporaneous and past NAO events:

$$\begin{aligned} log(L_{ct}) = \alpha &+ \sum_{\tau=0}^{N} \beta_\tau NAO_{t-\tau} \times \mathbb{I}_{c\epsilon NE} \\ &+ \sum_{\tau=0}^{N} \gamma_\tau NAO_{t-\tau} + \phi_t + \lambda_c + \varepsilon_{ct}. \end{aligned} \quad [2]$$

L_{ct} represents the labor variable of interest (wages, employment, or establishments) by county and year. I use an inverse hyperbolic sine[†] of the labor variable in the main specification to transform zeros in the data (38, 39). α is a constant and β_τ captures the linear effect of NAO τ periods ago on counties in New England (NE) compared to counties in the South Atlantic (SA). The treatment is NAO τ periods ago interacted with a dummy, $\mathbb{I}_{c\epsilon NE}$, that equals one for counties in NE and zero for counties in the SA. The AIC selects $N = 6$ as the best model for revenue, wages, and establishments. For consistency, I use this lag structure as the main specification for all of the outcome variables. ϕ_t are year fixed effects and λ_c are county fixed effects. I test for the assumed log-linear form of the model (*SI Appendix*, Fig. S1) as well as trending behavior (*SI Appendix*, Fig. S2). SEs are clustered at the county level to flexibly account for within-county, across-time correlation.

Because NAO has an annual resolution (Fig. 1*A*) and impacts the control and treatment regions, year fixed effects will be colinear with NAO and lagged NAO. For completeness, regional NAO and its lags are included in *SI Appendix*, Tables S16–S21 and show that coefficients for NAO and its lags were omitted due to colinearity with year fixed effects. The model can be rewritten as

$$log(L_{ct}) = \alpha + \sum_{\tau=0}^{N} \beta_\tau NAO_{t-\tau} \times \mathbb{I}_{c\epsilon NE} + \phi_t + \lambda_c + \varepsilon_{ct}. \quad [3]$$

For interpretation, I measure the cumulative impacts of NAO on labor from 1996 to 2017 by comparing the model with observed NAO to a model where NAO is constantly neutral (*SI Appendix*, section 7). Heterogeneous, county-level impacts are explored in *SI Appendix*, section 8.

Data Archival. All data and code necessary for replication of the results in this paper are available for download at GitHub.

ACKNOWLEDGMENTS. I thank Lee Anderson, Jim Berry, Anna Birkenbach, Matt Burgess, Mark Cane, Christopher Costello, Joshua Drew, Eyal Frank, Steve Gaines, Geoffrey Heal, Solomon Hsiang, Amir Jina, Kyle Meng, Carlos Moffat, John Mutter, Will Oremus, James Rising, and Wolfram Schlenker for their helpful comments and suggestions; and Min-Yang Lee, Eric Thunberg, Vanessa Zemke, and Daniel Tropper for their expertise in the data collection process.

[†] $ln(L + \sqrt{1 + L^2}) \rightarrow ln(2L)$.

1. Food and Agriculture Organization, *The State of World Fisheries and Aquaculture* (Food and Agriculture Organization of the United Nations, 2014).
2. A. J. Pershing *et al.*, Slow adaptation in the face of rapid warming leads to collapse of the Gulf of Maine cod fishery. *Science* **350**, 809–812 (2015).
3. C. M. Free *et al.*, Impacts of historical warming on marine fisheries production. *Science* **363**, 979–983 (2019).
4. M. L. Pinsky, B. Worm, M. J. Fogarty, J. L. Sarmiento, S. A. Levin, Marine taxa track local climate velocities. *Science* **341**, 1239–1242 (2013).
5. J. García Molinos *et al.*, Climate velocity and the future global redistribution of marine biodiversity. *Nat. Clim. Chang.* **6**, 83–88 (2015).
6. A. Le Bris *et al.*, Climate vulnerability and resilience in the most valuable North American fishery. *Proc. Natl. Acad. Sci. U.S.A.* **115**, 1831–1836 (2018).
7. K. C. Meng, K. L. Oremus, S. D. Gaines, New England cod collapse and the climate. *PLoS One* **11**, 1–10 (2016).
8. R. T. Carson, C. Granger, J. Jackson, W. Schlenker, Fisheries management under cyclical population dynamics. *Environ. Resour. Econ.* **42**, 379–410 (2009).
9. M. Memarzadeh, G. L. Britten, B. Worm, C. Boettiger, Rebuilding global fisheries under uncertainty. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 15985–15990 (2019).
10. U. Rashid Sumaila, W. W. L. Cheung, V. W. Y. Lam, D. Pauly, S. Herrick, Climate change impacts on the biophysics and economics of world fisheries. *Nat. Clim. Chang.* **1**, 449–456 (2011).
11. V. W. Y. Lam, W. W. L Cheung, G. Reygondeau, U. R. Sumaila, Projected change in global fisheries revenues under climate change. *Sci. Rep.* **6**, 32607 (2016).
12. S. D. Gaines *et al.*, Improved fisheries management could offset many negative effects of climate change. *Sci. Adv.* **1**, eaao1378 (2018).
13. S. Kaur, Nominal wage rigidity in village labor markets. *Am. Econ. Rev.* **109**, 3585–3616 (2019).
14. R. Hornbeck, The enduring impact of the American dust bowl: Short- and long-run adjustments to environmental catastrophe. *Am. Econ. Rev.* **102**, 1477–1507 (2012).
15. V. A. Mueller, D. E. Osgood, Long-term impacts of droughts on labour markets in developing countries: Evidence from Brazil. *J. Dev. Stud.* **45**, 1651–1662 (2009).
16. National Marine Fisheries Service, "Fisheries economics of the United States, 2016" (NOAA Tech. Memo. NMFS-F/SPO-187, US Department of Commerce, Silver Spring, MD, 2018).
17. L. Jewett, A. Romanou, "Ocean acidification and other ocean changes" in *Climate Science Special Report: Fourth National Climate Assessment*, D. J. Wuebbles *et al.*, Eds. (US Global Change Research Program, Washington, DC, 2017), vol. I, pp. 364–392.
18. M. Kurlansky, *Cod* (Random House, 1997).
19. S. Hsiang, Climate econometrics. *Annu. Rev. Resour. Econ.* **8**, 43–75 (2016).
20. G. Ottersen *et al.*, Ecological effects of the North Atlantic oscillation. *Oecologia* **128**, 1–14 (2001).
21. L. C. Stige, G. Otterson, K. Brander, K.-S. Chan, N. C. Stenseth, Cod and climate: Effect of the North Atlantic oscillation on recruitment in the North Atlantic. *Mar. Ecol. Prog. Ser.* **325**, 227–241 (2006).
22. G. D. McCarthy, I. D. Haigh, J. J.-M. Hirschi, J. P. Grist, D. A. Smeed, Ocean impact on decadal Atlantic climate variability revealed by sea-level observations. *Nature* **521**, 508–510 (2015).
23. T. L. Delworth *et al.*, The North Atlantic oscillation as a driver of rapid climate change in the northern hemisphere. *Nat. Geosci.* **9**, 509–512 (2016).
24. N. C. Stenseth *et al.*, Ecological effects of climate fluctuations. *Science* **297**, 1292–1296 (2002).
25. C. L. MacKenzie Jr, M. Tarnowski, Large shifts in commercial landings of estuarine and bay bivalve mollusks in northeastern United States after 1980 with assessment of causes. *Mar. Fish. Rev.* **80**, 1–28 (2018).
26. A. Henry, J. Olson, "An overview of the survey on the socio-economic aspects of commercial fishing crew in the northeast" (NOAA Tech. Memo. NMFS-NE-230, US Department of Commerce, Woods Hole, MA, 2014).
27. J. W. Morley, R. D. Batt, M. L. Pinsky, Marine assemblages respond rapidly to winter climate variability. *Glob. Chang. Biol.* **23**, 2590–2601 (2016).
28. S. Cunningham, L. S. Bennear, M. D. Smith, Spillovers in regional fisheries management: Do catch shares cause leakage?*Land Econ.*, **92**, 344–362 (2016).
29. T. Young *et al.*, Adaptation strategies of coastal fishing communities as species shift poleward. *ICES J. Mar. Sci.* **76**, 93–103 (2019).
30. Greater Atlantic Regional Fisheries Office, Vessel permits data (2019). https://archive.fisheries.noaa.gov/garfo/aps/permits/data/index.html. Accessed 3 April 2019.
31. D. E. Schindler *et al.*, Population diversity and the portfolio effect in an exploited species. *Nature* **465**, 609–612 (2010).
32. J. W. Hurrell, Decadal trends in the North Atlantic oscillation: Regional temperatures and precipitation. *Science* **269**, 676–679 (1995).
33. National Oceanic and Atmospheric Administration, Annual commercial landing statistics (2019). https://foss.nmfs.noaa.gov/apexfoss/f?p=215:200:17022275054107:::::. Accessed 19 April 2019.
34. T. A. Carleton, S. M. Hsiang, Social and economic impacts of climate. *Science* **353**, aad9837 (2016).
35. M. Dell, B. F. Jones, B. A. Olken, Evidence from the last half century. *Am. Econ. J. Macroecon.* **4**, 66–95 (2012).
36. W. K. Newey, K. D. West, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55**, 703–708 (1987).
37. S. R. Cohodes, J. S. Goodman, Merit aid, college quality, and college completion: Massachusetts' Adams scholarship as an in-kind subsidy. *Am. Econ. J. Appl. Econ.* **6**, 251–285 (2014).
38. J. B. Burbidge, L. Magee, A. L. Robb, Alternative transformations to handle extreme values of the dependent variable. *J. Am. Stat. Assoc.* **83**, 123–127 (1988).
39. D. Card, S. DellaVigna, "What do editors maximize? Evidence from four leading economics journals" (National Bureau of Economic Research, Cambridge, MA, 2017).