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Publication Date
2021-03-01

DOI
10.1016/j.jeem.2021.102419

Commercial Fisheries & Local Economies

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January 7, 2025

Abstract

Commercial fisheries are often presumed to contribute meaningfully to local economies, despite a lack of supporting empirical evidence. We address this gap by estimating local economic effects from commercial fishing activity in Alaska. Using exogenous variation in fish stocks and prices, we find that a 10% increase in a community's annual resident fishery earnings leads to a corresponding 0.7% increase in resident income. This translates to an increase of 1.54 dollars in total income for each dollar increase in fisheries earnings. Our results demonstrate the potential for local benefits from commercial fishing through direct, indirect, and induced effects into other sectors. Moreover, our findings demonstrate the importance of local resource ownership for generating benefits for local economies.

JEL Classification: R12, R23, O11, Q22

Keywords: Renewable resources; Fisheries; Shift-share instrument; Leakage; Spillovers.

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1 Introduction

Do commercial fisheries contribute to local economies? The answer to this question is often presumed to be yes and plays an influential role in the decisions of policy makers, despite little empirical evidence to support this claim. This is surprising since natural resources are generally not guaranteed to contribute significantly to local economies (van der Ploeg, 2011; James and Aadland, 2011). Indeed, it is not uncommon to find resource-rich regions lacking the pre-conditions required for resources to contribute to local economies in a meaningful way (Tiebout, 1956; Swales, 2005; Kilkenny and Partridge, 2009). In this paper, we estimate direct and spillover effects from Alaskan commercial fisheries on local wages, employment, and income using a community-level panel dataset of commercial fishing and formal-sector employment records. We exploit exogenous variation in fish stocks and prices, and adapt the empirical methodology of Moretti (2010) by employing a shift-share instrument (Bartik, 1991) to address potential endogeneity concerns. Given the size and importance of the commercial fishing industry for coastal economies, empirical verification of the local economic benefits from commercial fisheries is long overdue.[1]

We provide empirical evidence demonstrating commercial fisheries contribute to local economies. We find that commercially exploited fish stocks have positive direct effects: additional fishing and processing crew are hired, and processed harvests produce more value added. We also find statistical evidence of employment spillovers from commercial fishing into non-fishing sectors: a 10% increase in annual fishery earnings leads to a 0.3% increase in employment, which translates to 7.12 jobs per million dollars of fishery earnings. Overall, we find an increase of one dollar in fisheries earnings results in an increase of total income by 1.54 dollars. Our empirical results also suggest that the primary channel through which spillover effects take place is the earnings of local commercial-fishing permit owners, as opposed to the delivery (or landing) of fish to local businesses for value-added processing.

Our findings have important implications for resource development policies. First, local economies can benefit from resource development, even if they lack ideal conditions for resources to contribute in a meaningful way. Indeed, while the size of the commercial

[1]In the United States, for instance, commercial fishing is a $150B industry and contributes more than 1% to the GDP of 12 coastal states (National Marine Fisheries Service, 2017).

fishing sector in Alaska is significant, spillover benefits may still come as a surprise, given that a large portion of intermediate inputs used in the production of seafood is imported, Alaskan residents make up only half the crew and one-third of the processing labor force, and Alaskan-owned fishing and processing permits account for only a small fraction of the value of processed and harvested fish. Nevertheless, the fraction of resource rents accruing to local owners does provide spillover benefits to local economies. Local permit ownership creates an opportunity for fishery earnings to be spent locally on goods and services, in addition to hiring local crew members—who in turn, are also more likely to spend their earnings locally. This creates an induced effect in the local economy. In contrast, the wage and ownership earnings from seafood processing tend to accrue to non-residents, who are less likely to spend their money locally, resulting in leakage from the local economy.

More broadly, policies aimed towards increasing local resource-extraction activities may not reinforce local economies if either (*i*) the local labor force is comprised primarily of non-resident/migrant workers, or (*ii*) residents do not have an ownership stake in their local resources. The former implication has considerable theoretical (e.g., Moretti, 2011; Kline and Moretti, 2014) and empirical (Partridge et al., 2009; Wrenn et al., 2015; Guettabi and James, 2020) support. The latter implication, while intuitive, has only recently gained attention. Indeed, while the local economic effects of non-renewable resource sectors have received considerable attention in the literature, the vast majority of this work investigates the economic effects of resource-extraction activities, as opposed to the economic effects from resource ownership (Marchand and Weber, 2018). One exception is a recent study by Brown et al. (2019), which demonstrates that royalty payments from oil and gas leases account for a large share of the total income effect of extraction. Indeed, Brown et al. (2019) find that that a one dollar increase in oil and gas royalties is associated with an increase of 1.49 cents in total income for the royalty owner's county. This is similar to the increase of 1.54 cents of total income we find are associated with a one dollar increase in local permit-owner earnings.

Finally, our findings add support to the idea that place-based policies—regardless of whether their focus is on resource development—must be tailored to local conditions (Bartik, 2020). That is, broad-based policies that treat local economies uniformly are not likely to perform well if local economies are heterogeneous. For example, our results demonstrate that conventional policies whose goal is to redirect the value of commercial fisheries landings to local economies—such as allocating individual processing quotas (Matulich et al., 1996; Matulich and Sever, 1999), imposing restrictions to deliver fish to particular ports (Cojocaru et al., 2019), and restricting the trade of individual fishing quotas (Kroetz et al., 2015)—may not produce their intended benefits. Indeed, heterogeneous effects suggest that communities with higher rates of local processor ownership and more dependence on the commercial fisheries sector are more likely to experience benefits from local commercial fishing landings. Thus, depending on local conditions, some communities may benefit from policies that favor local processing businesses and/or enhance forward-and-backward linkages across sectors, while others may benefit from policies aimed to attract or retain resident fishery permit owners. In other words, context matters when designing policy.

The remainder of the paper is organized as follows. In Section 2, we discuss the relevant literature, the nature of cross-sector spillovers, and details of the commercial fishing industry in Alaska. Section 3 describes our data and our empirical strategy. We present our results in Section 4, including extensions to test for heterogeneity and robustness. We conclude with a discussion of the implications and limitations of our work, in addition to opportunities for future research.

2 Conceptual Framework and Background

Local economic effects from natural resource development—such as oil and mineral extraction, commercial fishery catches, or agricultural harvests—are often described by their direct impact to the shocked sector, and spillover effects into other sectors via indirect and induced effects. We draw on this terminology and adapt it for our analysis. We consider direct effects to be changes within the resource sector. For example, direct effects from larger fish stocks include changes in wages and employment for fishing and processing crew, earnings for the owners of fishing and processing permits, and fisheries-tax revenues for local governments. We consider indirect effects to be changes in the sectors from which the resource sector purchases intermediate goods and services (i.e., backward linkages) and the sectors that use outputs from the resource sector as inputs (i.e., forward linkages). For fisheries, backward linkages include bait, fishing gear, and vessel repair/maintenance services while forward linkages include seafood wholesalers and retailers. We consider induced effects to be impacts to local firms from supplying goods and services to the beneficiaries of the direct and indirect income effects. For example, increased fishing crew and processing wages, permit-owner earnings, and government tax revenue from larger fish shocks are spent on local goods and services, thereby inducing a demand shock for local suppliers. The total effect of resource development is thus the sum of the direct effects and the spillovers from indirect and induced effects.

Generally speaking, the size of direct and spillover effects relies on a number of preconditions (Tiebout, 1956; Swales, 2005; Gunton, 2009; Kilkenny and Partridge, 2009). First, the resource sector must be large relative to the size of the economy as a whole in order to stimulate employment and wage growth that is large enough to spillover into other sectors through indirect and induced effects. However, even if a shock is large, the direct benefits for local residents may be small if in-migration or commuting is relatively easy and/or local residents lack the skills and expertise demanded by the shocked sector (Moretti, 2010). Second, the size of the indirect effect depends on the presence and strength of linkages between the resource sector and upstream and downstream firms in the area. The indirect effect is likely to be smaller if most of the inputs are imported from outside the region (Partridge et al., 2009). Third, the size of the induced effect depends on whether the beneficiaries of direct and indirect effects purchase locally produced goods and services.

Overall, communities that experience higher relative shocks, have significant inter-industrial linkages, and have several opportunities to spend earnings locally are the most likely to experience significant gains from natural resource development. Unfortunately, it is not uncommon to find examples—especially in developing countries—where local labor markets are thin, resource extraction firms are not locally owned, few backward or forward linkages exist, and almost no taxes are collected by the local government from resource extraction operations (van der Ploeg, 2011).

Determining whether commercial fisheries have direct and spillover benefits for local economies has implications both for communities considering effective economic development and for fisheries management tasked with balancing conservation and economic considerations. Much of the past work on this topic has been based on input-output (I/O) models, many of which report large effects of fishing activity into non-fishing sectors (for a review, see Seung and Waters, 2006).[2] The limitations of these models, however, have been well documented (e.g., West, 1999; Seung and Waters, 2006). To overcome these limitations, more sophisticated simulation methods have estimated multipliers for fisheries—e.g., Social Accounting Matrices and computable general equilibrium (CGE) models. For example, Seung and Waters (2010) and Seung et al. (2014) use a CGE framework to estimate the direct and multiplier effects of the seafood industry in Alaska. However, even more sophisticated simulations rely critically on assumptions around elasticity estimates drawn from the literature.

The discussion thus far suggests that the impact of the commercial fishery sector on local economies is largely an empirical question; however, retrospective econometric investigations of local economic impacts of commercial fisheries are relatively scarce. Instead, considerable attention has been paid to the local economic effects of non-renewable resource sectors, such as oil/gas production and mining.[3] However, local economic effects from commercial fisheries may differ from those of non-renewable resources for several reasons.

First, the physical processes that determine fluctuations in the resource stock are quite different. For example, fish stocks vary considerably both within and across years; thus, commercial fishing can be highly seasonal, which makes it difficult to support year-round jobs. It also means that commercial fishing earnings can be highly uncertain, which may dampen investment in upstream and downstream industries that rely primarily on the commercial fishing sector. At the same time, unlike non-renewable resources, fisheries can produce rents in perpetuity if managed sustainably, which may bolster investment in upstream and downstream industries.

Second, commercial fishing may attract workers from different labor markets than non-

[2]See Jacobsen et al. (2014) for a review of other studies using the I/O methodology to estimate multiplier effects from the fishing industry.

[3]Notable examples include Corden and Neary (1982); Carrington (1996); Black et al. (2005); Moretti (2010); Weber (2012); Loayza et al. (2013); Aragón and Rud (2013); Fleming and Measham (2014); Weber (2014); Weinstein (2014); Lee (2015); Munasib and Rickman (2015); Fleming and Measham (2015); Paredes et al. (2015); Jacobsen and Parker (2016); Komarek (2016); Tsvetkova and Partridge (2016); Feyrer et al. (2017); Maniloff and Mastromonaco (2017); Agerton et al. (2017); Weinstein et al. (2018). See Marchand and Weber (2018) for a recent comprehensive survey of this literature.

renewable sectors, who may have a different elasticity of supply. For example, there is a relatively high degree of geographic mobility of commercial fishing laborers, which means that labor tends to be fairly elastic; for instance, migrant workers often comprise a significant portion of the commercial fishing labor force in Alaska.

Finally, there are differences in the institutions that govern the exploitation of the resource stock. For example, in contrast to severed mineral rights, regulations that govern many commercial fisheries often require that the permit owners be on board the fishing vessel, which could reduce the incidence of absentee ownership and increase the potential for non-wage income to be spent locally. Thus, the local economic effects of commercial fisheries may be different from those of non-renewable resource sectors, and are likely context dependent.

While econometric investigations of local economic impacts of commercial fisheries are relatively few, there are two notable exceptions: Roy et al. (2009) and Seung (2008), both of which use time series approaches to assess the economic impacts of commercial fishing at rather large levels of aggregation. Seung (2008) estimates long-run employment impacts from the seafood-processing sector, focusing on two fishery-dependent regions in Alaska. Estimated impulse response functions indicate that shocks to seafood-processing labor have relatively small effects on non-seafood employment in the two study regions. Seung (2008) attributes the small impacts to the large proportion of labor, goods, and services imported by the seafood processing industry from outside the region. Roy et al. (2009) test the economic-base hypothesis (North, 1955; Tiebout, 1956) for the fishing industry in Newfoundland and finds that it is indeed an economic base, but the elasticity of the direct effect is not large. Our paper builds on Roy et al. (2009) and Seung (2008) by estimating the economic effect of commercial fishing empirically.

Our analysis differs by employing a panel data approach adapted from the regional economics literature (Moretti, 2010). Panel data allows us to analyze the economic effects of commercial fishing using both temporal and cross-sectional variation while controlling for unobservable year- and place-specific fixed effects that may be correlated with both commercial fishing activity and local economic outcomes. Further, the panel structure of our data allows us to examine heterogeneous effects across relatively smaller geographic units (i.e., communities).

Alaska provides a useful setting for estimating local fishing economic effects for several reasons. The size of the commercial fishing sector in Alaska is significant: Alaskan fisheries produced approximately \$4.4 billion in sales in 2015, ranking first in the U.S. in terms of production (National Marine Fisheries Service, 2017). Commercial fishing also plays a large role in the state economy, particularly in many Alaskan coastal communities.[4] However, Alaska also serves as an example of a resource-rich state that may lack the pre-conditions for resources to contribute to local economies in a meaningful way. For example, Guettabi and James (2020) demonstrate that while total employment increases with resource extraction activities in the oil-rich North Slope borough in Alaska, local residents receive little to none of these benefits. A similar story may be true of Alaska's fisheries. While Alaskan fishers represented 71% of permit owners in 2015, they earned only 33% of the total value of catch. (See Table B.1).[5] Further, only 65% of the wholesale value from commercial fisheries can be attributed to a processor based in Alaska.[6] Thus, a large portion of the value of commercial fisheries in Alaska may never enter into local economies.

There are also reasons to believe that the spillover benefits from commercial fishing activities that do enter local economies may be small. A large portion of intermediate inputs used in the production of seafood is imported to Alaska communities due to their remoteness—most goods and services used as intermediate inputs are imported primarily from Washington State (Seung, 2008). This means that an increase in demand from positive shocks to commercial fishing will induce imports rather than local impacts. Another reason relates to the residency status of factor payment recipients (e.g., fishing crew and processing labor) and the processing owners to whom profits are accruing. In fact, the fraction of Alaskan-owned fishing permits, crew and processing labor, and Alaskan-owned fishing firms

[4]For instance, commercial fishing was the state's largest employer in 2016: approximately 29,200 workers (8.8% of total non-farm employment) were directly employed in the commercial fishing sector, totaling \$824 million in labor income (McDowell Group, 2017). According to National Marine Fisheries Service (2017), Alaska was ranked fourth in seafood-industry employment, which includes the commercial harvesting and processing sectors, with approximately 60,000 employed. For comparison, California ranks first in terms of fishing employment with approximately twice as many workers as Alaska; however, this difference is striking when considering that California's economy is roughly 50 times larger than Alaska's.

[5]The largest share of earnings were owned by residents of Washington State (50%), who represented around 15% of permit owners.

[6]The rest of the wholesale value can largely be attributed to catcher processors, which catch and process fish on board the vessel while at sea.

that work and operate in the state is relatively small (Table B.1). Only half of the total crew jobs in Alaska accrue to local residents. Similarly, Alaskans are also in the minority of fish processing labor (just under 30% employees), earning just 35% of the wages paid to these positions. Finally, while Alaskans own the majority of fishing business licenses (nearly 80%), many of these are smaller catcher/seller operations. Only half of the processor permits are owned by Alaskans, and these businesses account for only 26% of the total wholesale value generated by Alaska fisheries. If most of the non-resident earnings leave the region, the induced and indirect effects of commercial fishing in local economies can be expected to be small. Altogether, Alaska provides an opportunity to test for local economic effects from a large and valuable resource sector, even if the ideal conditions are lacking for the resource sector to act as an economic base.

3 Empirical Strategy

Our estimation strategy and data allow us to distinguish the channels through which activity from a variety of fisheries around Alaska enter a community, how these activities spillover into other sectors of the local economy, and who is impacted from the direct and spillover effects. To understand how fishing activity enters a community, we separately estimate the effect of "resident earnings," or the revenues of local permit-owners from commercial fishing, and "local landings," or the value of received deliveries to local fish processors. We consider different forms of direct effects fishing activity may have on fishing crew, processing labor, and the value added from processing. To understand how activities spillover into other sectors, we measure impacts on different economic outcomes, such wages, employment, and income across different sectors of the local economy. Finally, to understand who benefits from commercial fishing, we are careful to identify if those impacted by commercial fishing are local residents or commuters/migrants.

3.1 Estimation and Identification

Our empirical strategy is adapted from Moretti (2010), who tests for labor impacts from shocks in the traded sector to the non-traded sector. In similar fashion, we test for effects from shocks in commercial fishing earnings and landings on the fishery sector itself and other industries in both the traded (e.g., manufacturing or fish processing) and non-traded (e.g., restaurants, retail, etc.) sectors. We estimate the model:

$$\Delta \, ln \, y_{ct} = \beta \Delta \, ln \, x_{ct} + \tau_t + \alpha_c + \epsilon_{ct} \tag{1}$$

where $\Delta \, ln \, y_{ct}$ is the change in the log outcome variable of interest for community c from year $t-1$ to year t, $\Delta \, ln \, x_{ct}$ is the annual change in the log value of fisheries activity (catch by residents or landings to local processors) in community c, τ_t is an annual fixed effect, and α_c is a community fixed effect.[7] A given community may harvest or receive deliveries from a number of fisheries across different species and areas, so when considering total resident catch or total local landings measured by x_{ct}, we aggregate across all fisheries. The coefficient β reflects the percentage change in a given outcome stemming from a one-percent change in the measure of commercial fisheries value. An estimate of zero implies that commercial fisheries have no effect in the sector of the local economy represented by the outcome variable y.

One possible concern with estimating Eq. 1 using ordinary least squares is that commercial fishing activity measured at the community level may be endogenous: fishing decisions, such as how much to harvest or where to deliver harvest, may depend on community- and time-specific unobservable factors that are correlated with local economic outcomes, thereby creating a simultaneity bias in our estimate of β. For example, higher wages in the non-fishing sectors driven by unobservable factors may result in capital purchases in the fishing industry (e.g., gear and entry permits), thereby creating a positive simultaneity bias in the estimate of β. On the other hand, these same non-fishing shocks also increase the opportunity cost of commercial-fishing participation, thereby creating a negative simultaneity bias in β. Non-fishing economic shocks may also affect the amount of fish landed in a community if such shocks influence processing costs, and in turn, the prices that fish processors are able to offer fishers. While the inclusion of community fixed effects and annual fixed effects par-

[7]For example, one such annual fixed effect is the annual lump-sum distribution of the Alaska Permanent Fund Dividend. Recent work on the impacts of the dividend include investigations of its effect on the labor market (Jones and Marinescu, 2018; Bibler et al., 2019) and its effect on crime (Watson et al., 2020).

tially addresses these endogeneity concerns, they do not address any potential endogeneity stemming from community- and annual-specific unobserved factors.

We address these concerns by recognizing that the two most important factors influencing overall commercial fishing earnings and landings are stock levels (the total volume of fish biomass) and global fish prices, both of which are exogenously determined from the perspective of an individual community. By employing a shift-share instrumental variable (IV) strategy, we isolate exogenous variation in commercial-fishing outcomes that stems from changes in overall fish stocks and prices, thereby disposing of any endogenous variation in commercial-fishing outcomes that stems from fishing decisions. The shift-share (or Bartik, 1991) instrument is a popular approach for dealing with potential endogeneity issues when attempting to identify a causal relationship between two variables at the regional level—e.g., local labor-market effects from immigration (Card, 2001), trade (Autor et al., 2013), or total factor productivity (Hornbeck and Moretti, 2019) shocks. The underlying motivation behind the shift-share instrument is a simple accounting identity that allows a sector's regional growth rate to be decomposed into a nation-wide sectoral growth rate and an idiosyncratic sector-regional growth rate. Under the assumption that nation-wide growth rates are exogenous from the perspective of a region, a sector's nation-wide growth rate can be used as an instrument for a sector's regional growth rate.

We exploit the fact that, just as the growth rate of a community's economy is derived from multiple sectors, the growth rate of a community's commercial fishing earnings (or landings) is derived from multiple fisheries, each of which differs by species, geography, and gear, and experiences shocks from fluctuations in biological stocks and global prices. Thus, the growth rate of commercial fishing earnings (or landings) in community c at time t can be expressed as $\Delta x_{ct} = \sum_j w_{cjt} \Delta x_{cjt}$, where Δx_{cjt} is the growth rate of earnings in fishery j in community c at time t, and w_{cjt} is the share of community c's commercial fishing earnings attributable to fishery j at time t. To address the potential endogeneity of Δx_{cjt}, we make use of the accounting identity to decompose fishery-community earnings growth as $\Delta x_{cjt} = \Delta x_{jt} + (\Delta x_{cjt} - \Delta x_{jt})$, where $\Delta x_{jt} = \sum_c \Delta x_{cjt}$ is the fishery-wide component of earnings growth from fishery j (across all communities) and the term in the parentheses is the idiosyncratic component of fishery-community earnings growth. The shift-share instrument is a weighted sum of the fishery-wide component of the growth rates with fishery-community shares as weights: $z_{ct} = \sum_j w_{cj0} \Delta x_{jt}$, where we follow standard practice and fix fishery-community shares at their pre-sample levels.[8] In essence, we use the overall growth rate that would have occurred in a community if its earnings from a given fishery grew at the fishery's overall growth rate. Our instrument is therefore exploiting variation in the overall growth rate for each fishery (the "shift"), weighted by a fishery's historical importance to a community's commercial fishing earnings (the "share").

We estimate Eq. 1 by two-stage least squares, with the first stage specified by:

$$\Delta \, ln \, x_{ct} = \gamma \, ln \, z_{ct} + \tau_t + \alpha_c + \epsilon_{ct}, \tag{2}$$

where γ is the first-stage relationship between the shift-share instrument z_{ct} and fishing activity growth $\Delta \, ln \, x_{ct}$, while τ_t and α_c are time and community fixed effects, respectively. We also estimate Eq. 1 by OLS for reference. Recent work provides more rigorous scrutiny of the identification assumptions underlying the Bartik instrument (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2018). In Section 4.5, we discuss our instrument's identifying assumptions in the context of this recent work and present evidence for its validity.

Finally, annual commercial fishery measures are more variable for those communities with relatively small amounts of fishing activity. To address such heteroskedasticity in the first-stage regression of our IV estimator, we weight each observation by their place-specific sample average of commercial-fishing activity. For example, for analyses using resident earnings at the community level, the sample average of resident earnings for each community is used as the regression weight. This places relatively larger weight on those communities where commercial-fishing activity is greater and variation in aggregate fishing outcomes is more systematic.

[8] Since our sample of economic outcome data begins in 2000 we define the pre-sample period for the community-specific weight, w_{jc0}, as the average over 1998-2000. A three-year period is likely long enough to smooth across fishery-related shocks that occurred in a particular year, but short enough to exclude structural changes that may have occurred in earlier years.

3.2 Data

We assemble a dataset of economic and commercial fishing variables for all Alaskan communities that engaged in commercial fisheries in some form over the period 1998-2015. Data on received earnings from permit-owners come from the Alaska Commercial Fisheries Entry Commission (CFEC) Basic Information Tables for the years 1998-2015. These data provide near-comprehensive coverage of permit-owner harvests and earnings across commercial fisheries in the state, reported annually for each community-fishery pair. Alaskan commercial fisheries are stipulated by species, fishing district, and gear type. Any individual that partakes in commercial-fishing activity requires a fishery-specific permit issued by the CFEC. In 2010, 20,275 CFEC permits were issued across 205 fisheries in Alaska.[9,10] A permit-owner's community is determined based on the address listed on a fisher's permit. Data on the value of received deliveries to a local processor are aggregated from individual deliveries reported as a part of the Alaska Department of Fish and Game's (ADF&G) fish tickets and eLandings systems.

We use several outcome variables to investigate the local economic effects of commercial fishing activity. We test for the direct effect of commercial fishing activity on three outcomes: harvesting crew which catch fish at sea; processing labor which cleans, fillets and packs the fish; and processing value added, which measures the net value of the products. We also test for spillover effects of fishing activity using outcomes on wages, employment (disaggregated to traded and non-traded sectors), and new hiring in non-fishing sectors of the economy. Finally,

[9] CFEC data do not include harvests and earnings in fisheries for which the harvest is not landed in an Alaskan port. The number of such fisheries across the state are few and are dominated by large out-of-state catcher-processors (CPs) that process their catch at sea; thus, their direct impact on the economies of most Alaskan communities is likely limited due to the lack of landings that take place and the lack of permit-owners that reside in Alaska. Of the $4.2B in first wholesale value of Alaska-region fisheries, $1.3B was generated by CP vessels (McDowell Group, 2017). Nevertheless, the main ports that service such CPs (e.g., Dutch Harbor, Atka, and Akutan) are likely positively impacted by this fleet, and previous work has demonstrated that the CP sector is an important contributor to the Alaskan economy (Waters et al., 2014); thus, our estimates are likely biased downwards.

[10] Note that for a small subset of community-fishery observations, earnings values are censored to protect confidentiality. Censoring occurs when fewer than four fishers participate in a given fishery. In the case where only one fishery in a community is censored, earnings values for other fisheries are also censored so that a community total can be reported. For the 18,940 fisher-community-year triads, 1,851 are censored in this way. These censored observations represent less than 1% of total earnings. When earnings values are censored, we impute them with one of three methods based on the nature of uncensored observations available. For robustness, we also estimate our models by dropping the censored observations and find that the results are similar. See Appendix A for more details.

we estimate the total effect (direct plus spillover effects) of commercial fishing activity using gross income. Data available to measure these outcomes varies in geographic aggregation. Many outcome variables are available at the community level (e.g., fishing crew, employment, wages, and value added) while several others are available only at higher levels of geographic aggregation, such as the borough level (e.g., gross income) or regional level (e.g., processing labor). Boroughs are Alaska's county equivalent and regions are a collection of boroughs defined by Alaska Department of Labor and Workforce Development (AKDOL) for the purpose of maintaining confidentiality.[11]

To measure direct effects, data on the number of registered crew licenses at the community level is recorded by ADF&G and were obtained from NOAA's Alaska Fisheries Science Center's (AFSC) Community Profiles and Snapshots. To our knowledge, there is no comprehensive available data on the wages earned by crew members in the commercial fishing industry.[12] Data on the number of processing laborers come from the Alaska Department of Labor and Workforce Development Research and Analysis Section. These data are only available at the regional level. Data on the wholesale value of seafood products at the community level come from ADF&G's Commercial Operator's Annual Reports (COAR).[13]

To measure spillover effects, we collect data on local economic outcomes from the AKDOL's Alaska Local and Regional Information (ALARI) database. These data cover the years 2000-2015. Commonly used data on annual wages and employment in rural areas often do not report statistics below the level of the county, but ALARI reports data for each of Alaska's 344 communities. This match is enabled by AKDOL linking unemployment insurance records—the same records that are used by the Bureau of Labor Statistic's (BLS) Quarterly Census of Employment and Wages (QCEW)—with other administrative data collected by the state.

Unlike QCEW, however, ALARI reports wages and employment by the employee's place of residence rather than their place of work. However, AKDOL does not publish wages

[11] A map of these eight regions and the boroughs they nest are available on the AKDOL website live.laborstats.alaska.gov/seafood/

[12] There are some exceptions for a subset of the fisheries in Alaska—e.g., the nine rationalized crab fisheries, two of which were investigated by (Abbott et al., 2010).

[13] Fish ticket/eLandings and COAR data are confidential and were obtained as part of a cooperative agreement between the University of Alaska Anchorage and NOAA's AFSC.

and employment by community of work to maintain confidentiality for employers. ALARI also identifies the number of new hires in each community in a given year, defined as an employee who was not working for the employer in any of the four previous quarters. Further, ALARI usefully reports employment by industry, which we aggregate into traded sectors (agriculture, natural resources and mining, and manufacturing) and non-traded sectors (all other industries).

In addition, we can test for spillover effects both at the place-of-residence and for place-of-work; however, place-of-work data come from BLS's QCEW and are only available at the borough level. For comparison, we aggregate place-of-residence wage and employment data from the ALARI community-level data to the borough level.

Finally, to capture the total income effect of commercial fisheries on local economies, we use adjusted gross income data from the Internal Revenue Service (IRS) county-level database—which includes income for individuals without wage and salary earnings—into our analysis. Note, however, that taxable income will not include under-the-table cash payments or barter arrangements, which may be used in the informal economy of our setting.

It is important to note both ALARI and QCEW are based on unemployment insurance records. Commercial fishers and crew engaged in harvesting are mostly self-employed or contract workers, and therefore, are not included in these measures. Additionally, wages for other upstream/downstream proprietors and self-employed individuals are also not covered by unemployment insurance. In contrast, wage and employment records for workers employed by commercial processors are included in ALARI and QCEW measures as part of the traded-sector. This distinction is important when differentiating between direct- and spillover-induced effects on wages and employment. It is also worth noting that our measures of fishing crew, processor labor, and employment measured in ALARI account for the number of workers, not the number of full-time equivalent (FTE) jobs. The seafood industry in Alaska is mostly seasonal (with a summer peak between June and September), with many workers only working a few months out of the year. This is important for comparing our estimates to other studies that use FTE jobs as their dependent variable of interest.

Because our analysis is based on relative changes year-over-year, communities or boroughs which did not harvest catch in the state or receive landings at a local port for at least two consecutive years (141 in communities and 4 boroughs) were excluded from the sample. The omitted communities are generally inland and small, with an average population of 340. In total, 200 communities and 25 boroughs have sufficient data over the sample period to estimate the economic effect of fishery permit-owner earnings. Likewise, 69 communities and 18 boroughs had sufficient data to assess the economic effect of commercial-fishery landings. Across communities and boroughs, there is considerable variation in both the economic outcome variables and the measures of fishing activity. Table B.2 presents summary statistics for the main variables used in the analysis. The average community and year have wages of just over \$54 million per year and with approximately 1,350 persons employed. These jobs are heavily weighted toward the non-traded sector and vary considerably across communities.

Year-to-year shocks to fisheries value can be quite large in magnitude due to shifts in prices and the biological stocks of individual species over space. Figure B.1 illustrates this variation. Figure 1 shows the spatial variation of catch and landings averaged over the period 2000-2015 at both the community and borough levels. At the community level (Panels a and b), fishing activity is concentrated in Southeastern Alaska, on the Kenai Peninsula south of Anchorage, and across the Alaska Peninsula between Anchorage and the large port town of Unalaska (Dutch Harbor). Revenues from catch and particularly landings are more sparse along the western coast, the area of the state with a number of smaller communities. Looking at per-capita activity at the borough level (Panels e and f), shows a similar distribution of activity.

4 Results

We estimate Eq. 1 using several different dependent variables, which vary by their geographic aggregation (community, borough, or region) due to data availability. Whether our estimated effect represents a direct effect, spillover effect, or total effect depends on the dependent variable. The β's estimated for each outcome by Eq. 1 are elasticities, but as in Moretti (2010), we transform the estimated elasticities and their associated 95% confidence intervals into level changes. The units of these level changes are in terms of dollars-per-dollar or jobs-per-dollar (denoted $\Delta Y/\$$ in the tables below), depending on the dependent variable y.

This transformation takes the form $\Delta Y/\$ = \hat{\beta}\frac{\overline{y}}{\overline{x}}$, where $\overline{y}$ and $\overline{x}$ are the sample mean values of outcome y and fishery activity x, respectively.

We first present estimates of direct effects of commercial fishing and processing sectors. We then test for spillover effects of commercial fishing activity into other industries. Next, we show the effect of commercial fishing on total income (both fishing and non-fishing). We then explore the potential mechanisms for these effects by testing whether direct and spillover effects from commercial fishing are different for resident and non-resident workers. We also test for heterogeneous effects by narrowing our sample on communities with locally-owned processing capacity and for "fishing-dependent" communities. Finally, we assess the validity of our instrument and robustness of our findings across different model specifications.

4.1 Direct effects of commercial fishing

We first focus our attention on estimating direct effects from commercial fishing. Direct effects are represented by: fishing crew employment, which is a primary input into fishing production; processing labor, which is a primary input into processing production; and the value-added (wholesale revenue minus ex-vessel revenue) of local processing plants. Crew labor and processor value added data are available at the community level, but processor labor is only reported at the aggregated region level. There are only eight of these regions, which notably reduces the sample size and reduces statistical power.

We find that local crew license registrations increase by 0.27% and 0.18% in response to a 1% increase in the value of resident catch and local landings, respectively, providing evidence that resident permit owners are responsive to increases in harvest opportunities by hiring local crew (Table 1). These elasticities imply that a \$1 million increase in resident catch or local landings results in additional local crew hires of 3.4 and 1.36, respectively. We also find that the value added from processors increases by 0.75% and 0.60% in response to a 1% increase in the value of resident catch and local landings. In levels, each dollar of landings creates an additional \$0.49 of value added. Processing labor increases by 0.46% for a 1% increase in local landings, which is approximately 9 jobs for every million dollars landed locally. We note that crew effects are larger where permit-owners live (resident catch) as opposed to where harvest is landed (local landings). Conversely, and intuitively, processing labor is not statistically responsive to where permit-owners live, but instead, where they land their harvest.

4.2 Spillover effects of commercial fishing

How do the direct effects to the commercial fishing industry in Table 1 translate to spillover effects in other sectors? Table 2 presents estimates of commercial-fishing effects on wages, employment (overall, traded sector, and non-traded sector) and new hires for resident workers at the community level. Resident workers include all employees who lived in a community in a given year and participated in unemployment insurance. Non-resident employees, either those who reside outside Alaska or in a different Alaska community, are not represented in these estimates. We find statistically significant employment impacts from resident catch earnings: a 1% change in the value of resident catch leads to a 0.03% change in resident employment. We find similar results for the value of local landings: a 1% change in local deliveries values leads to a 0.04% change in resident employment. Translated to jobs-per-dollar, these equate to 7.2 and 2 resident jobs created for every million dollars of resident catch or local landings, respectively. Effects on wages and new hires are statistically insignificant for both resident catch earnings and local landings.

We note that these outcome variables are inclusive of all employment covered by unemployment insurance, which does not include employment in the harvesting (captain and crew labor) sector, but does include employment in the fish processing sector. However, despite the fact that traded-sector employment includes resident processing employment, our estimates of traded-sector employment effects are virtually zero for both resident catch earnings and local landings.[14] Instead, our estimated resident employment impacts for are driven by the non-traded sector, suggesting that the total employment estimates are not driven by direct effects from resident processing labor.

A lack of resident wages and traded-sector employment impacts could be due to the processing sector crowding out labor from other traded industries, like mining. It is also possible that resident workers shifting from unemployed to employed in processing are offset

[14]Fish processing is a subset of manufacturing, and we classify that sector as part of the larger traded good sector.

by resident workers shifting from processing to harvesting (where their labor is uncovered by unemployment insurance used to measure employment here). However, as we discuss in more detail in Section 4.4, the null effect for resident wages and trade-sector employment is likely driven by our finding that the primary processing-labor response is driven by non-resident workers.

Interestingly, our empirical estimates of spillover effects are consistent with previous CGE simulation investigations of Alaska's commercial fisheries. Seung et al. (2014) finds that for a 1% increase in the volume of catch, employment in non-fishing sectors increases by 0.03%. Note that Seung et al. looks at shocks to the volume of catch, while we look at the value of catch. Also, Seung et al. consider total catch and employment from any residency status, whereas our estimates are for residents only.

Our estimates of employment spillover effects are also similar to those found for non-renewable resources. For example, the 1.98 jobs per million dollars of local landings we find is comparable to the 2.35 jobs per million dollars of natural gas production found by Weber (2012) for Colorado, Texas and Wyoming, and the 0.85 jobs per million dollars of oil and gas production found by Feyrer et al. (2017) at the national level. In contrast, our insignificant estimate for wage spillover effects from local landings (and resident earnings) differ from those found by Weber (2012) and Feyrer et al. (2017): 0.09 and 0.07 dollars per dollar of oil and gas production, respectively. However, the estimates of employment and wage effects in Weber (2012) and Feyrer et al. (2017) are not perfect comparisons to ours given that (*i*) they include jobs for both residents and non-residents (as opposed to just residents), (*ii*) they include jobs created in both the directly and indirectly impacted sectors (as opposed to just indirectly impacted sectors), and (*iii*) the estimates are at the county level (as opposed to the community level). Together, these suggest that the number of jobs created from local fishing activity, particularly from resident earnings, could be considerably larger than those found for non-renewable resource production.

4.3 Total effects of commercial fishing

To estimate the total effect (direct plus spillover effects) from commercial fishing, we use taxable income at the borough level, reported as adjustable gross income (AGI) by the IRS, as our dependent variable. Included in AGI is fisher earnings, crew wages, and processing wages for residents, as is any income generated by borough residents through spillover activities into upstream or downstream industries. The total effect estimate therefore reflects the total income effect to all residents in a borough. As shown in Table 3, we find a 0.07% increase in AGI from a 1% increase in the value of resident catch. In contrast, we do not find any statistical evidence of a total effect on resident income from commercial fishery landings. Each dollar increase of resident catch results in an increase of 1.54 dollars of AGI for the borough. A value greater than one implies the presence of spillovers from fishing into the broader economy. Since AGI is net of certain tax deductions, this estimate represents a lower bound on the multiplier effect (i.e., the accounting relationship where the same dollar is on the right- and left-hand sides of an equation).

For comparison, our estimates for catch-induced income effects are similar to the CGE simulation results reported by Seung et al. (2014): a 1% increase in catch increases income by 0.06%, which is comparable to our estimated elasticity of 0.07. Examining the total effects of royalty payments from oil and gas leases on county income, Brown et al. (2019) finds that one dollar of royalty payments generates 1.49 dollars of AGI in the lease-owner's county of residence (but not necessarily where the oil and gas production occurred), which is comparable to our estimate of 1.54 dollars of AGI per million dollars of resident catch. Looking at the location of the activity, as opposed to the residency of the owner, Feyrer et al. (2017) finds that one dollar of additional oil and gas production results in 0.18 dollars of AGI in the producing county, which is comparable to the (insignificant) 0.07 dollars of AGI per million dollars of local landings.

4.4 Exploring Mechanisms

Distinguishing between the location of resource extraction and the location of resource ownership appears to be an important factor in explaining the effects of natural resource sectors on local economies, both for commercial fisheries and non-renewable resources. In this section, we explore possible explanations for this result. A key finding is local landings do not appear to create additional processing jobs for residents; rather, they tend to create processing employment for non-resident workers, who may take their earnings home at the end of the season, rather than spending them locally. We also find suggestive evidence that communities with processing facilities owned by an Alaskan resident are more likely to hire local workers. Finally, we show that communities with more economic dependence on commercial fisheries tend to experience larger spillover effects, both from local landings and from resident earnings.

We first explore whether direct effects of fishing activity differentially impact residents and non-residents. The only direct effect for which this differentiation is possible, due to available data, is processing labor at the regional level. Table 4 presents these estimated effects. We find that additional catch or landings have no significant effect for the number of residents hired for processing in that region. However, we find that additional landings do generate significant non-resident processing labor jobs. This pattern in processing-labor residency could have negative implications for local induced effects from fisheries landings if non-residents (particularly seasonal workers) save their earnings to take home outside Alaska, rather than spend them in the local economy.[15]

While non-resident workers can stunt spillover effects, so can non-resident owners. By construction, resident catch earnings are all owned locally, but there is varying resident ownership in capital for processors. We explore whether direct and spillover effects are influenced by resident ownership of seafood processing plants. Resident-owned processors may have different preferences for sourcing labor and other inputs locally, and could have a larger induced effect if business earnings are spent on local goods and services. From the COAR database, we can differentiate between businesses registered to Alaskan owners versus those owned outside the state. We subset our data by communities in which 100% of processors are Alaska-owned versus those with some out-of-state ownership, which splits the sample roughly in half. Intuitively, processor ownership has negligible influence on the impacts resulting from resident catch; however, we find suggestive evidence that processing activities from local landings generate larger employment impacts in communities where processors are resident owned (Figure 2).[16]

[15]We also test for residency-specific spillover effects by measuring wages and employment by both place-of-work and place-of-residence. However, because data limits such an analysis to the borough level, we find there is a lack of sufficient power to detect meaningful economic effects. Full details are provided in Appendix Section C.

[16]Note that the sub-sample of communities with 100% resident ownership of processors tend to have

Local economies may also vary in their degree of dependence on commercial fisheries, reflecting differences in economic structures across communities. Fisheries-dependent communities could exhibit greater forward and backward linkages between the fisheries sector, which could lead to larger indirect effects. Further, shocks to the fisheries sector could be larger relative to the size of the local economy for such communities.

We explore how our estimated direct and spillover effects differ across a community's dependence on commercial fishing. For this analysis, we use two different definitions of dependence: (1) an index of fishing engagement, and (2) the ratio of resident commercial catch revenue to total formal employment wages. The fishing-engagement index was constructed by Himes-Cornell and Kasperski (2016), and measures a community's fishing dependence on a 0-5 scale, with 5 being the most dependent and 0 the least. The score is derived from summing 5 binary indicators which measure engagement in commercial, recreational, and subsistence fishing. We estimate our model on different sub-samples of our data, progressively dropping lower-scoring communities and concentrating the sample on more fishing-dependent communities. For the most fishing-dependent communities (those with scores of 4 and 5), there is some evidence of larger wage and employment effects (Figure 3). There is also some evidence of smaller direct effects of resident catch and local landings on fishing crew jobs in more fishing-dependent communities, which suggests that any spillover effects in these communities are likely not being driven by increased crew opportunities for residents.

Results using our second measure of fishing dependence (i.e., the ratio of fishing revenue to total wages) are quite similar to those presented above.[17,18]

Altogether, our results here suggest that context matters for understanding how commercial fisheries contribute to local economies. Indeed, our finding that local landings have relatively small spillover and total effects (Tables 2 and 3) may not have anything to do with the seafood-processing production technology itself, but rather be due to the residency of the

smaller and more variable amounts of resident catch and landings. As a result, the first stage regressions for this sub-sample have poorer fit, and in turn, confidence intervals for the IV estimates are considerably larger than corresponding estimates using the full sample.

[17] Results using our second measure of fishing dependence are presented in Appendix Figure B.2. To subset our sample for this heterogeneity analysis, we drop communities progressively below certain decile thresholds of this dependency measure (50th, 60th, 70th, 80th).

[18] We also explored other dimensions of heterogeneity but found no compelling evidence for such effects. These included differentiation by urban and rural communities and degree of fishery seasonality.

laborers and owners of the processing facilities. Thus, communities with higher rates of local processor workers/owners and more dependence on commercial fisheries may in fact benefit from policies directed towards increasing the value of commercially landed harvests. Moreover, our results here confirm the importance of worker and owner residency for generating spillover benefits in local economies.

4.5 Robustness and Instrument Validation

To assess the robustness of our findings, we systematically estimate a number of different model specifications for both resident catch and local landings. Figure D.3 shows the robustness of the community-level results to eight alternative model specifications: fixed effects (none, community only, annual only), unclustered standard errors, unweighted regressions, dropping outliers with annual changes in fishing activity larger than 200% or larger than 100%, and the use of a Van Dijk (2018) correction to the shift-share instrument.[19] Generally speaking, the results are qualitatively similar across these outcomes and specifications, with two exceptions. First, the van Dijk shift-share instrument correction reduces the first-stage fit for local landings, because a given fishery's landings tend to be more concentrated in the number of ports that receive deliveries. As a result, the precision of our second-stage estimates is reduced, as reflected in the large confidence intervals. In addition, our estimates tend to increase considerably in (absolute) size. Second, unweighted regressions also tend to reduce the first-stage fit, which is to be expected given that relatively more weight is now placed on communities with less systematic variation in fisheries activity. In turn, our second-stage estimates are less precise (particularly for local landings), and result in notably larger effects for crew labor and smaller estimates for wages and employment.

We also conduct a falsification test, described in more detail in Appendix Section D.2, to provide evidence that we are correctly interpreting the causal direction of our estimated effects. We adopt the spirit of the falsification test used by Autor et al. (2013) in their study of the effect of contemporaneous Chinese imports on contemporaneous US manufacturing

[19]Van Dijk (2018) proposes an alternative formulation of the shift-share instrument, which leaves out a location's own contribution to the shift instrument to address any endogeneity concerns that could arise if a region's growth rate makes up a significant portion of the national growth rate. The van Dijk correction is the preferred specification for our borough-level total income results.

employment. In their setting, Autor et al. (2013) are concerned that the fall in US manufacturing employment could have caused the rise in Chinese imports, or that there exists some unobserved common factor responsible for both. To address this concern, Autor et al. (2013) estimate the effect of *past* manufacturing employment on *current* Chinese imports as a falsification test. In our setting, we may also be concerned that our results are not capturing contemporaneous effects of fishing activity on local economic activity, but rather some long-run common causal factor behind both. Following Autor et al. (2013), we regress past economic activity on current fisheries activity. We find that past (and future) economic outcomes correlate poorly to current fishing activity (Figures D.4 and D.5), which provides additional evidence for our interpretation of the causal direction of our estimates.

To demonstrate the validity of our instrument, we refer to recent work that provides more rigorous scrutiny of the identification assumptions underlying the Bartik instrument, particularly with respect to the properties for exogeneity of the "shares" component (Goldsmith-Pinkham et al., 2020) and the "shifts" component (Borusyak et al., 2018) of the instrument. An important insight from this work is that exogeneity of one component (shares or shifts) can be sufficient for the validity of the overall shift-share IV approach. In particular, Borusyak et al. (2018) demonstrate that the shift-share instrument is valid when shocks are quasi-randomly assigned to industries (fisheries in our case), when the number of independent shifts gets large relative to the sample, and when variation in the shift-share instrument is not driven by a finite set of industries (fisheries). Given the large number of fisheries in our setting (205), all of which incur large and stochastic shocks, we focus on exploiting exogeneity in the shifts as the primary source of identification.

In consideration of the source of variation in our 205 shift instruments, approximately 60% of the variation in the total value of fishing earnings or landings comes from variation in prices, while 40% comes from variation in harvest quantities. The variation in prices is driven by national and global demand factors, such as national income and exchange rates, as well as the global markets for substitute products.[20] But prices vary mostly across species and over time, rather than across regions within Alaska. Variation in harvest quantities is both regional and temporal, and is driven principally by biomass shocks to a fishery's target

[20] Approximately two-thirds of Alaskan seafood is exported internationally (McDowell Group, 2017).

species. An individual community has a negligible influence on a species' biomass growth rate, as each individual community represents only a small portion for each fishery's overall earnings. In fact, as we show in Appendix Table B.1, out-of-state fishers account for 66% of total earnings from Alaska's fisheries. Thus, from the perspective of an Alaskan community, shocks to an overall fishery's value, either through prices or quantities, can be considered quasi-randomly assigned.

Appendix Section D.3 describes in detail validation assessments for the instrument. To determine whether variation in our shift-share instrument is driven by a small number of shift instruments, we plot the cumulative density function of each fishery's share of community earnings in Figure D.6 and conclude that a diverse group of species make up most community's fishery portfolios—i.e., a small hand-full of fisheries do not drive the earnings for most communities. In fact, in the most extreme case of portfolio concentration, only 10% of communities receive more than 50% of their total earnings from a single fishery (the halibut longline fishery for vessels under 60'). Each of the shift instruments also display a considerable amount of variation and tend to be relatively uncorrelated with each other, as shown by plots of the coefficient of variation and pair-wise correlation coefficients between fisheries in Figure D.7. Finally, to verify that no single fishery dominates variation in the shift-share instrument or single-handedly influences our estimated elasticities, we investigate the sensitivity of our first- and second-stage estimates to iteratively dropping the 10 highest-value fisheries from the analysis (Table D.4 and Figure D.8). Altogether, our shift-share instrument exhibits properties consistent with those outlined in Borusyak et al. (2018), and we interpret our estimates as stemming from exogenous variation in stock levels and global seafood prices.

5 Conclusion

We evaluate how variation in a valuable renewable resource affects local economies in Alaska. Despite the sizable literature that estimates the direct and spillover effects of non-renewable resources, such as oil and natural gas, this paper makes a first attempt of providing retrospective and econometric estimates of local direct and spillovers from commercial fisheries using panel-data methods. We adapt a shift-share instrument approach to a commercial fisheries setting, which allows us to exploit exogenous variation in fishery earnings and landings from 205 different fisheries. We find that direct effects and spillovers occur as a result of fluctuations in commercial fishing activity, despite the fact that industrial linkages are few and that the non-resident labor force is high in many communities.

Our results document an important pattern of how resource extraction activity enters a community. We show that outcomes for local residents are more closely tied to the location of resource and capital ownership, as opposed to the location where activity takes place. This is similar to the pattern documented by Brown et al. (2019) for oil and gas drilling. While delivering landings to processors in a community does boost processing labor there, these workers are mostly non-residents of Alaska. Consequently, we also show smaller spillover and total effects from local landings than for resident-owned catch. However, when more processing capital is owned locally, we find larger spillover effects. Together, these findings suggest fishery and development policy aimed at increasing economic opportunity for local residents should consider the residency of resource and capital owners, not simply the presence of activity.

There are some issues our analysis is not able to address. First, our estimated effects are local to the variation in fish stocks that we observe in our sample, which likely represents fluctuations around a steady state. However, fluctuation in fish stocks is projected to become more extreme in the long run as a result of climate change and corresponding changes to ocean conditions and habitats. Our analysis is therefore limited in answering questions that are more short-run in nature. For example, the question of how much worse-off a community would be if a fishery permanently collapsed is one our analysis does not address. The most notable example of such a collapse is the indefinite closure of the North Atlantic cod fisheries in the early 1990s, which largely remain closed today (Rose and Rowe, 2015). Similarly, our analysis does not estimate the effects of a "fisheries boom" or the case where a natural resource is newly discovered or exploitable, which is more frequently addressed by papers related to non-renewable resources. Our analysis also has some limitations that would benefit from future research. Our study estimates the effect of commercial fishing activity, omitting important recreational and subsistence activities. Future work that examines other forms of fishing activities and incorporates impacts on these sectors would be able to provide a more comprehensive outlook on the contribution of fish stocks to local economies.

Finally, our results provide guidance for economic development for small fishing communities in particular, but also rural communities more generally. While many Alaskan fishing communities are rural and isolated, they are not unrecognizable from small communities in other locations. Our results suggest that while increasing activity in the economic base sector has the potential for short-term benefits, governments, management institutions, and economic development organizations must tailor policies and practices to local conditions (Bartik, 2020). The heterogeneity of results across communities suggest that development policies will not necessarily be effective for all communities. Indeed, depending on the residency of local workers and resource owners, some communities may benefit from policies that favor local extraction firms and/or enhance forward-and-backward linkages across sectors, while others may benefit from policies aimed to attract or retain local workers and resource owners.

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Tables

Table 1: Direct Effects of Fishing Activity

	Resident Catch					
	Community				Region	
	Resident Crew		Value Added		Processing Labor	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Elasticity Catch	0.152***	0.273***	0.375***	0.752***	0.008	0.163
	(0.040)	(0.060)	(0.125)	(0.176)	(0.156)	(0.422)
$\Delta Y/\$$ Catch	1.89	3.40	0.44	0.88	0.22	3.17
95% CI	[0.9,2.87]	[1.94,4.85]	[0.15,0.73]	[0.48,1.29]	[-8.67,9.11]	[-12.95,19.28]
First-stage F		92.82		109.87		13.66
N Places	197	197	59	59	8	8
Observations	2,310	2,310	610	610	106	106
	Local Landings					
Elasticity Landings	−0.042	0.183***	0.069	0.599***	0.149**	0.460**
	(0.036)	(0.071)	(0.103)	(0.202)	(0.059)	(0.184)
$\Delta Y/\$$ Landings	-0.31	1.36	0.06	0.49	4.13	9.20
95% CI	[-0.83,0.21]	[0.33,2.39]	[-0.11,0.22]	[0.17,0.82]	[0.95,7.31]	[1.99,16.41]
First-stage F		41.61		56.57		13.98
N Places	69	69	52	52	8	8
Observations	929	929	566	566	106	106
Place Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
van Dijk	No	No	No	No	No	No

Note: *p<0.1; **p<0.05; ***p<0.01. Errors clustered at the community level. Elasticities are estimated β coefficients from Eq. 1; $\Delta Y/\$ = \hat{\beta}\frac{\overline{y}}{\overline{x}}$, where $\overline{y}$ and $\overline{x}$ are the sample mean values of outcome y and fishery activity x, respectively. Resident crew are the number of licensed crew members who reside in a community. Value added is the difference in wholesale value created by processors in a community and ex-vessel value of landings in a community. Processing labor is the total of annual processing jobs in a region. Units for the $\Delta Y/\$$ estimates for crew and processing labor are jobs per million dollars of fishing activity. Units for the $\Delta Y/\$$ estimates for value added are dollars of value added per dollar of fishing activity. Regressions weighted by average fishing activity by community across time. Sample period is 2001-2015. Pre-sample period for IV construction is 1998-2000. van Dijk first-stage correction subtracts own-catch from fishery earnings in first-stage.

Table 2: Spillover Effects of Catch and Landings at the Community Level

	Resident Catch									
					Employment					
	Wages		Employment		Traded		Non-Traded		New Hires	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Elasticity Catch	0.017**	0.015	0.015**	0.027*	0.027	−0.002	0.019***	0.028*	−0.010	−0.016
	(0.007)	(0.011)	(0.006)	(0.016)	(0.030)	(0.060)	(0.007)	(0.015)	(0.029)	(0.058)
$\Delta Y/\$$ Catch	0.19	0.17	4.08	7.12	0.54	-0.04	4.62	6.97	-0.84	-1.38
95% CI	[0.03,0.35]	[-0.08,0.42]	[0.7,7.46]	[-1.22,15.45]	[-0.63,1.72]	[-2.41,2.33]	[1.22,8.02]	[-0.35,14.29]	[-5.73,4.04]	[-11.18,8.43]
First-stage F		101.09		101.09		101.09		101.09		138.39
N Places	200	200	200	200	200	200	200	200	200	200
Observations	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,161	2,161
	Local Landings									
Elasticity Landings	0.012	0.003	−0.001	0.042**	−0.045	−0.047	0.011*	0.040**	−0.034	0.056
	(0.009)	(0.028)	(0.008)	(0.019)	(0.029)	(0.071)	(0.006)	(0.017)	(0.025)	(0.094)
$\Delta Y/\$$ Landings	0.02	0.00	-0.05	1.98	-0.32	-0.34	0.42	1.61	-0.50	0.84
95% CI	[-0.01,0.05]	[-0.09,0.1]	[-0.77,0.66]	[0.18,3.77]	[-0.72,0.08]	[-1.33,0.65]	[-0.05,0.9]	[0.27,2.94]	[-1.23,0.22]	[-1.94,3.62]
First-stage F		39.93		39.93		39.93		39.93		31.48
N Places	69	69	69	69	69	69	69	69	69	69
Observations	995	995	995	995	995	995	995	995	861	861
Place Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
van Dijk	No	No	No	No	No	No	No	No	No	No

Note: *p<0.1; **p<0.05; ***p<0.01. Errors clustered at the community level. Elasticities are estimated β coefficients from Eq. 1; $\Delta Y/\$ = \hat{\beta}\frac{\overline{y}}{\overline{x}}$, where $\overline{y}$ and $\overline{x}$ are the sample mean values of outcome y and fishery activity x, respectively. Wages are the total wages of community residents. Employment is the total number of unique jobs held by community residents. Traded and non-traded employment is employment decomposed into these respective sectors. New hires are the number of newly created positions that community residents were hired into. Units for the $\Delta Y/\$$ estimates for wages are dollars per dollar of fishing activity. Units for the $\Delta Y/\$$ estimates for employment and new hires are jobs per million dollars of fishing activity. Regressions weighted by average fishing activity by community across time. Sample period is 2001-2015. Pre-sample period for IV construction is 1998-2000. van Dijk first-stage correction subtracts own-catch from fishery earnings in first-stage.

Table 3: Total Income Effects of Fishing Activity

	Resident Catch	
	Borough	
	IRS AGI	
	OLS (1)	IV (2)
Elasticity Catch	0.064***	0.069**
	(0.020)	(0.027)
$\Delta Y/\$$ Catch	1.44	1.54
95% CI	[0.55,2.32]	[0.37,2.72]
First-stage F		89.43
N Places	25	25
Observations	327	327
	Local Landings	
Elasticity Landings	0.019	0.011
	(0.014)	(0.062)
$\Delta Y/\$$ Landings	0.12	0.07
95% CI	[-0.05,0.29]	[-0.69,0.83]
First-stage F		20.51
N Places	18	18
Observations	239	239
Place Effects	Yes	Yes
Year Effects	Yes	Yes
van Dijk	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Errors clustered at the borough level. Elasticities are estimated β coefficients from Eq. 1; $\Delta Y/\$ = \hat{\beta}\frac{\overline{y}}{\overline{x}}$, where $\overline{y}$ and $\overline{x}$ are the sample mean values of outcome y and fishery activity x, respectively. IRS AGI is the adjusted gross income reported in tax filings by residents of a given borough. Units for the $\Delta Y/\$$ estimates are dollars per dollar of fishing activity. Regressions weighted by average fishing activity by borough across time. Sample period is 2001-2015. Pre-sample period for IV construction is 1998-2000. van Dijk first-stage correction subtracts own-catch from fishery earnings in first-stage.

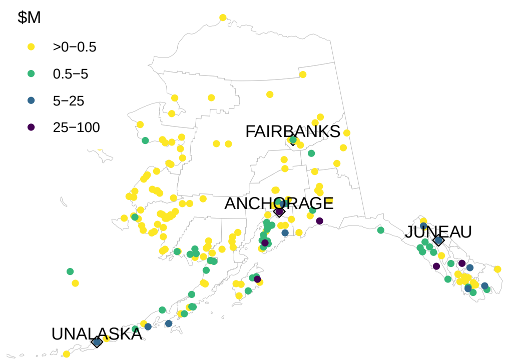
Table 4: Processing Labor Effects by Alaska Residency

	Resident Catch			
	AK Resident		Non-Resident	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Elasticity Catch	-0.029	-0.440	-0.029	0.493
	(0.147)	(0.410)	(0.211)	(0.585)
$\Delta Y/\$$ Catch	-0.24	-11.76	-1.37	5.27
95% CI	[-3.01,2.53]	[-35.23,11.71]	[-9.47,6.73]	[-5.99,16.52]
First-stage F		13.66		13.66
N Places	8	8	8	8
Observations	106	106	106	106
	Local Landings			
Elasticity Landings	-0.051	0.077	0.221^{***}	0.572^{**}
	(0.045)	(0.126)	(0.083)	(0.241)
$\Delta Y/\$$ Landings	-0.38	2.65	4.24	4.61
95% CI	[-1.07,0.31]	[-4.51,9.8]	[0.92,7.56]	[0.75,8.47]
First-stage F		13.98		13.98
N Places	8	8	8	8
Observations	106	106	106	106
Place Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
van Dijk	No	No	No	No

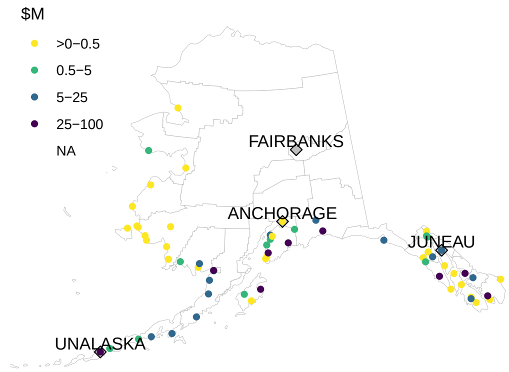
Note: *p<0.1; **p<0.05; ***p<0.01. Elasticities are estimated β coefficients from Eq. 1; $\Delta Y/\$ = \hat{\beta}\frac{\overline{y}}{\overline{x}}$, where $\overline{y}$ and $\overline{x}$ are the sample mean values of outcome y and fishery activity x, respectively. Units for the $\Delta Y/\$$ estimates for fish processing are jobs per million dollars of fishing activity. Regressions weighted by average fishing activity by region across time. Sample period is 2001-2015. Pre-sample period for IV construction is 1998-2000.

Figures

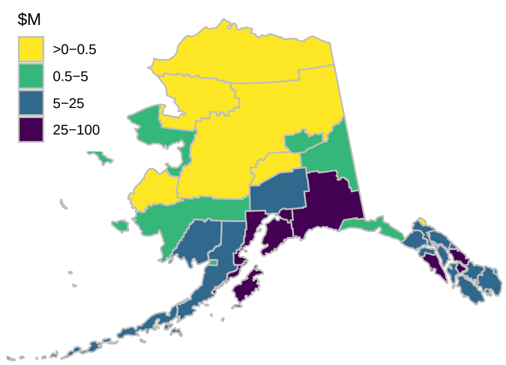
Figure 1: Average Fishing Activity Across Alaska



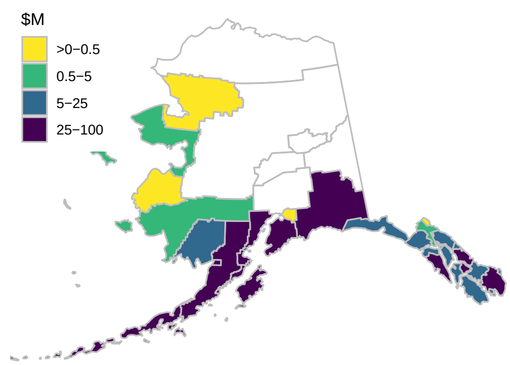
a) Community Resident Catch



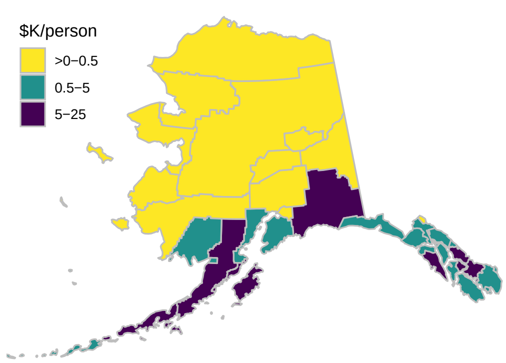
b) Community Local Landings



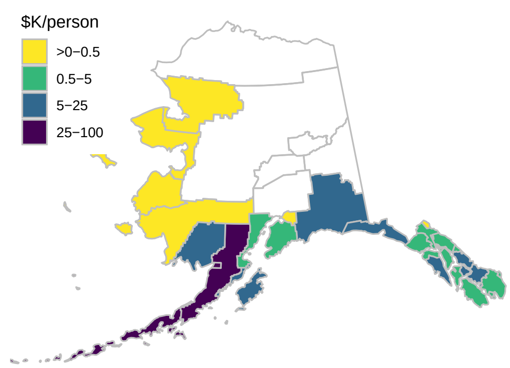
c) Borough Resident Catch



d) Borough Local Landings



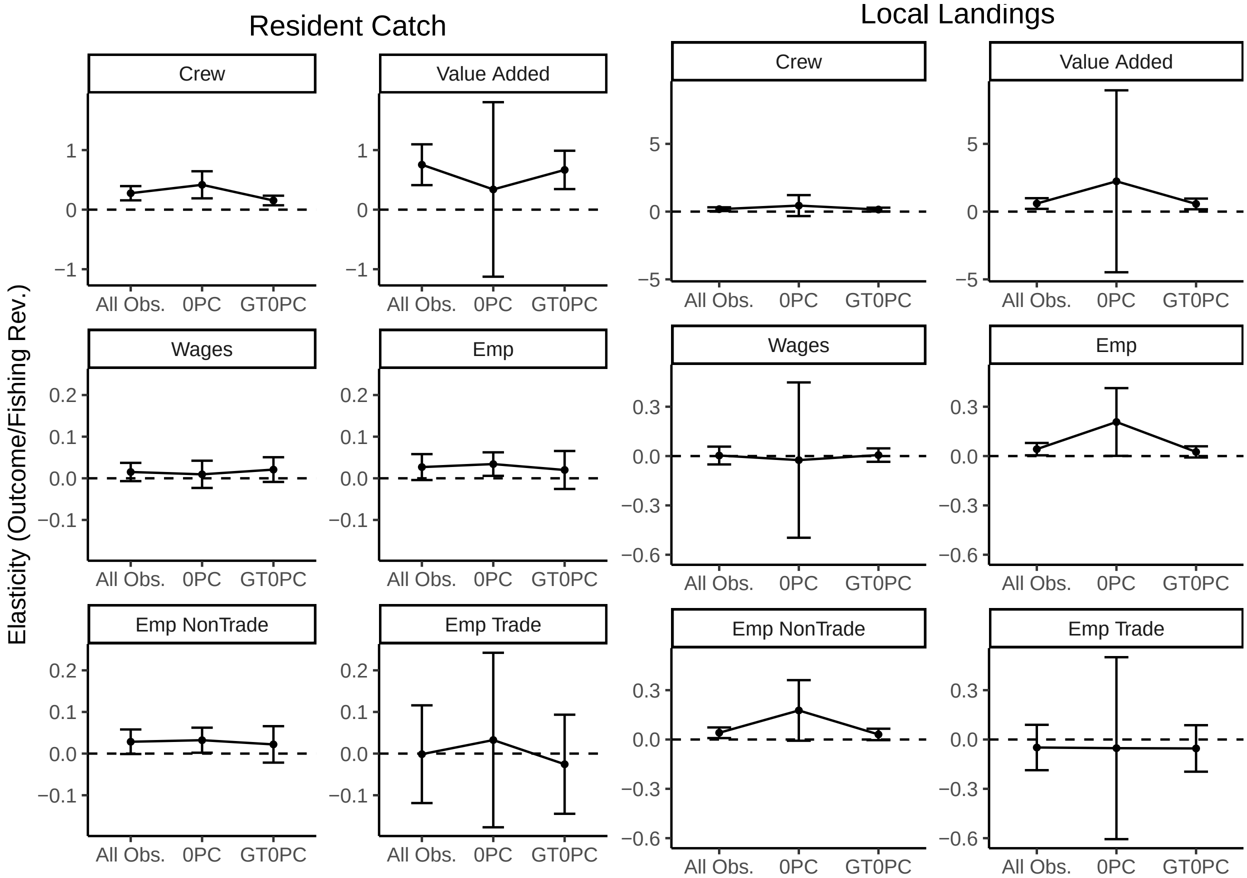
e) Borough Resident Catch Per Capita



f) Borough Local Landings Per Capita

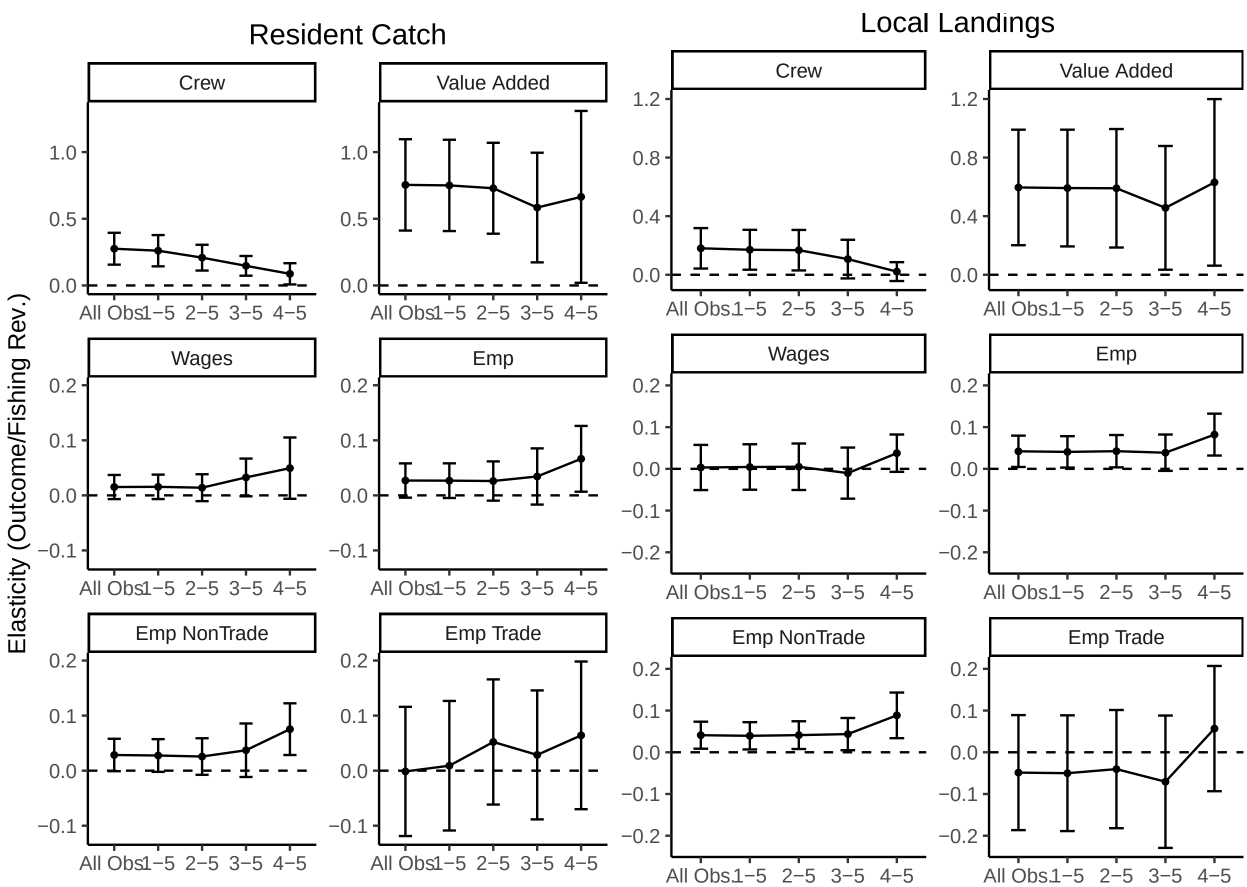
Map shows the annual average fishing ex-vessel values at the community and borough level. Community-level of aggregation is shown in upper panels (a) and (b). Borough-level aggregation is shown in panels (c) through (f). Resident catch in left panels (a), (c), and (e) is the total ex-vessel value of harvest from permit holders residing in the community or borough. Local landings in right panels (b), (d) and (f) are the total ex-vessel value of fish landed at a processor or fish buyer in a community or borough.

Figure 2: Heterogeneity by ownership of local processors



Coefficient estimates and 95% confidence intervals are estimated by 2SLS from Eqs. 1 on three subsets of the data. All observations contains the full sample; "0PC" denotes communities with zero percent out-of-state processor ownership; "GT0PC" denotes communities for which there is greater than zero percent out-of-state ownership.

Figure 3: Heterogeneity by community dependence on the fishing industry



Coefficient estimates and 95% confidence intervals are estimated by 2SLS from Eqs. 1 on subsets of the data. From left to right, we gradually drop less fishery-dependent communities. Fishery dependency indices are calculated by Himes-Cornell and Kasperski (2016), and are a scale of 1 (least dependent) to 5 (most depednent).

Appendix A Data Imputation

For a small subset of community-fishery observations, earnings values are censored to protect confidentiality. Censoring occurs when fewer than four fishers participate in a given fishery. In the case where only one fishery in a community is censored, earnings values for another fishery are also censored so that a community total can be reported. When catch values are censored we impute them with one of three methods based on the nature of uncensored observations available. First, even when annual earnings values are censored, we still observe the number of fishers in a community who fished that year. Our imputation calculates average per-fisher earnings, then multiplies this by the number of fishers. If data are not available for a more data-intense imputation for a given observation, we use the next-most data intense method. From least to most data intense these imputations are:

1. Average earnings-per-fisher for the fishery in a given year. Calculated based on CFEC's total earnings for the fishery in a given year divided by the number of fishers who fished. This assumes that a given community's earnings per fisher are the same as other communities.

2. When at least one community-fishery observation is uncensored, we can improve the imputation in (1) by adjusting the simple average with a community-specific production factor. We use available earnings observations to calculate the ratio of a community's earnings-per-fisher to the average earning-per-fisher for the entire fishery. We multiply (1) by this ratio.

3. When censored observations are infrequent over time for a community, we average the imputation developed in (2) with a lead and lag of the missing observation. This allows us to capture single period shocks and community-specific trends.

For robustness, we also estimate our models by dropping the censored observations and find that the results are similar.

Appendix B Supplemental Tables and Figures

Table B.1 describes the residence status (Alaskan or non-Alaskan) of various fishing activity. It highlights that a majority of ex-vessel earnings for fishers and processor wholesale value is owned by non-residents of Alaska.

Table B.2 presents summary statistics on the fishing activity and economic outcomes aggregated at the community and borough levels, the primary geographic units of analysis.

Year-to-year shocks to fisheries value can be quite large in magnitude due to shifts in prices and the biological stocks of individual species over space. Figure B.1 illustrates this variation. In a given year, some communities experience positive shocks, while others experience negative shocks. The large, heterogeneous shocks across time and across space provide useful variation for identification, given that fisheries shocks can be separated from common macro-economic trends.

In Section 4.4 we investigated how fisheries-dependent communities could exhibit greater forward and backward linkages between the fisheries sector, which could lead to larger indirect effects. In main text Figure 3 we show such effects using a fishing-engagement index constructed by Himes-Cornell and Kasperski (2016). Here we present an alternative for measuring fisheries dependence based on relative wages to fishing income. First, we calculate the ratio of unemployment insurance-eligible resident wages to the total fishing earnings in a community. We then group communities using decile bins across this ratio. Results using our second measure of fishing dependence are presented in Figure B.2. To subset our sample for this heterogeneity analysis, we drop communities progressively below certain decile thresholds of this dependency measure (50th, 60th, 70th, 80th). Results are consident with those we present in the main text.

Table B.1: Fishing Activity by Residency Status

	Alaskan Residents	Non-Residents	Total	% Alaskan
Harvest[1]				
Fishers (who fished)	6,923	2,838	9,761	71%
Earnings (Million $)	602	1,213	1,815	33%
Crew Licenses	9,566	8,328	17,894	53%
Processing Labor[2]				
Workers	7,875	19,086	26,961	29%
Worker Wages (Million $)	146	267	413	35%
Downstream Ownership[3]				
All Fishery Business Licenses	890	251	1141	78%
Processing Licenses[4]	152	150	302	50%
Wholesale Value (Million $)[5]	655	3,518	4,173	16%

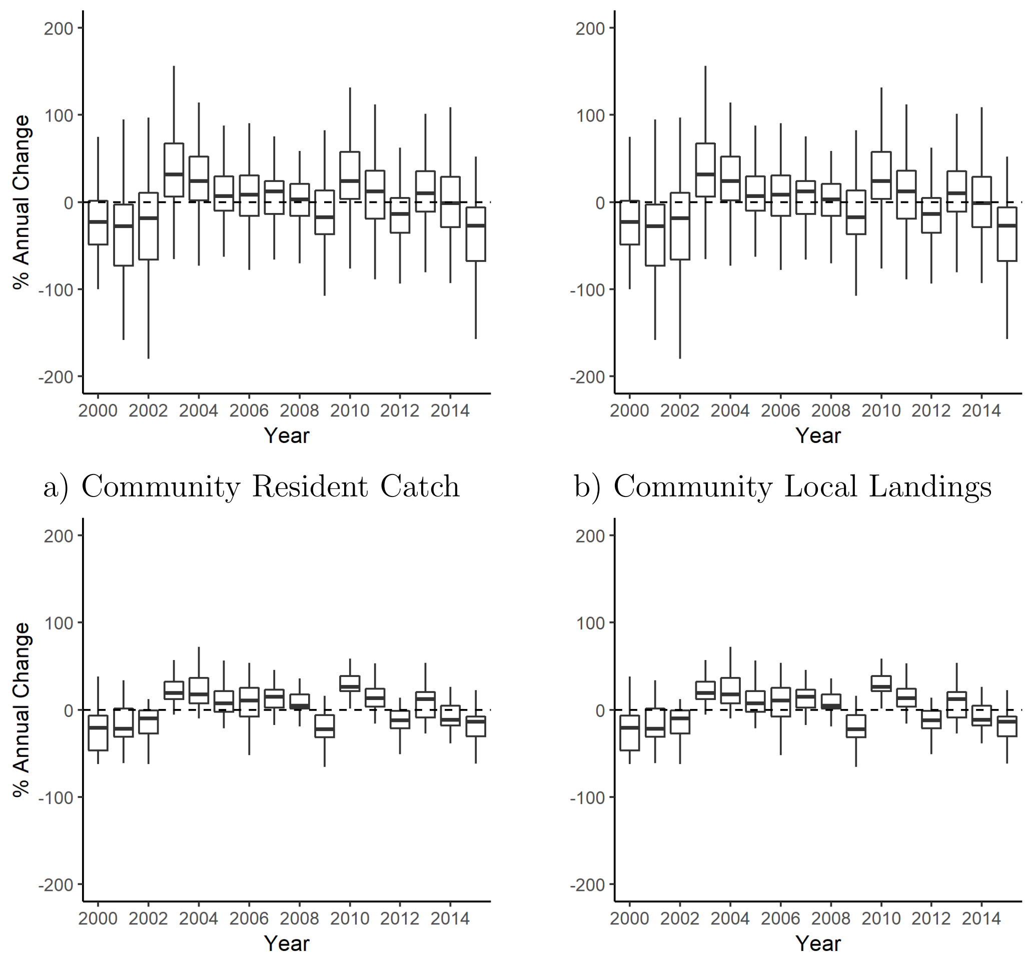
[1] Fisherman number and earnings from CFEC basic information tables (totals for all fisheries), 2015 data. Crew license data from Tide (2007).
[2] Processing labor from "Seafood Processing Workforce" report, Alaska DOL Research and Analysis Section, 2015 data.
[3] License ownership data from Alaska DFG, "Commercial Permit and License Holders Listing," 2015 data.
[4] We define processing licenses as Shore-based Processors, Catcher/Processors, Floating Processors, and EEZ Only.
[5] Wholesale value reported as part of "Commercial Operator's Annual Reports Data." This value includes both shore-based and vessel processing.

Table B.2: Summary Statistics

Community Level					
	N	Mean	St. Dev.	Min	Max
Total Wages (2015 $1k)	2,496	54,193	435,488	44	6,336,780
Employment	2,496	1,346	9,837	5	131,962
New Hires	2,496	452	3,281	0	48,658
Employment: Traded	2,496	96	549	0	7,582
Employment: NonTraded	2,496	1,251	9,300	4	124,364
Crew Licenses	2,310	67	152	0	1,420
Wholesale Value Added (2015 $1k)	2,282	7,996	30,143	0	322,496
Total Resident Catch (2015 $1k)	2,496	3,187	11,347	0	122,715
Total Local Landings (2015 $1k)	2,496	4,492	15,306	0	198,306
Catch/Wages (%)	2,496	37	110	0	1,560
Landings/Wages (%)	2,496	65	482	0	12,610
Borough Level					
Gross Income (AGI) (2015 $1m)	392	695	1,769	9	11,909
Total Wages, Residents (2015 $1k)	425	376,793	962,601	6,808	6,336,780
Employment, Residents (1,000)	425	11	24	0	132
Total Wages, Workers (2015 $1,000)	392	531,419	1,361,501	9,034	8,782,783
Employment, Workers (1,000)	392	12	28	0	154
Crew Licenses	425	367	397	0	1,959
Wholesale Value Added (2015 $1k)	282	31,451	72,396	0	402,468
Total Resident Catch (2015 $1k)	425	17,774	25,261	1	132,320
Total Local Landings (2015 $1k)	425	23,780	32,616	0	154,571

N is the number of non-NA observations for each variable. Total wages and employment at the community level and total wages and employment for residents (res) at the borough level are from AKDOL's ALARI database. New hires and sectoral employment are also from ALARI. ALARI data correspond to formal sector employment where the employer files unemployment insurance. Total resident catch is total ex-vessel value of commercial fish harvested by residents. Total local landings are the total ex-vessel value of fish landed at a processor or fish buyer in a community or borough. Gross Income is adjusted gross income of residents of the borough from the U.S. IRS. Employment and Wages by place of work come from the U.S. BLS's QCEW. Crew licenses are the number of registered commercial fishing crew living in a jurisdiction; these data come from NOAA's Alaska Fisheries Science Centers Community Profiles and Snapshot. Wholesale Value Added is the difference between wholesale value produced from processors (as reported by ADFG COAR) and the ex-vessel value of landings.

Figure B.1: Variation in Ex-vessel Value of Resident Catch and Local Landings at the Community and Borough Level

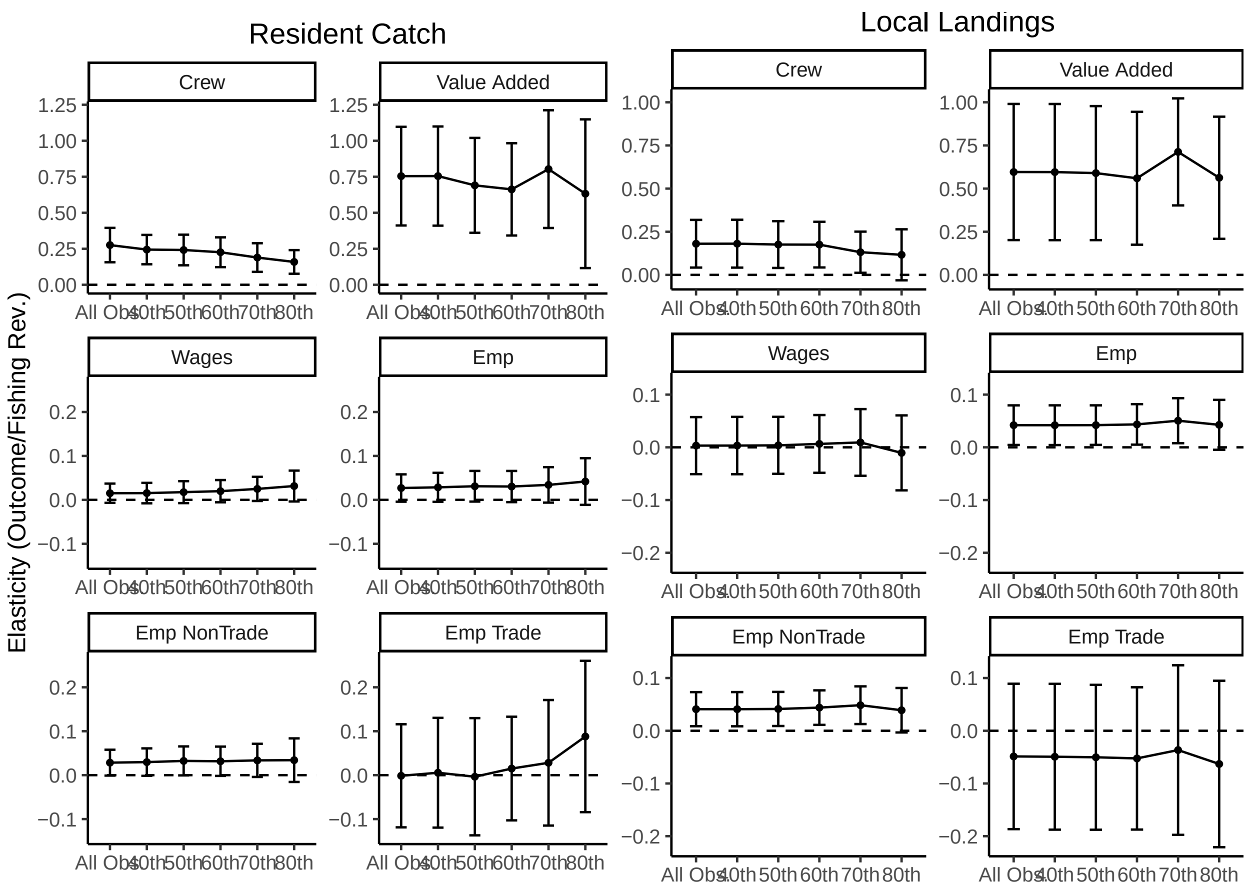


a) Community Resident Catch b) Community Local Landings

c) Borough Resident Catch d) Borough Local Landings

Box and whiskers showing the distribution of the % change in total ex-vessel values from the previous year. Whiskers extend to 1.5x the inter-quartile range (i.e., the distance between the first and third quartiles). Community-level aggregation is shown in upper panels (a) and (b). Borough-level aggregation is shown in lower panels (c) and (d). Resident catch in panels (a) and (c) is the total ex-vessel value of harvest from permit holders residing in the community or borough. Local landings in panels (b) and (d) are the total ex-vessel value of fish landed at a processor or fish buyer in a community or borough.

Figure B.2: Heterogeneity by fishing dependence (catch/wages)



Coefficient estimates and 95% confidence intervals for model estimated on subsets of the data. From left to right, we gradually drop less fishery-dependent communities. Fishery dependency indices are calculated by the ratio of fishing income to wages in a community, and indexed based on deciles. The rightmost estimate in each panel corresponds to the communities in only the top two deciles of the ratio of fishing income to wages.

Appendix C Spillover Effects by Residency

In Table C.3, we compare estimated effects on non-fishing wages and employment measured by place-of-residence and place-of-work at the borough level. Estimated effects that are larger for place-of-work would suggest that spillover benefits from commercial fishing are accruing to non-resident workers. The lack of statistically significant results for both place-of-residence and place-of-work measurements, however, suggests that neither residents nor non-residents experience wage or employment effects from commercial fishing in non-fishing sectors at this level of aggregation. One potential concern here is a lack of sufficient power to detect meaningful economic effects at the borough level. Indeed, a post-hoc power analysis indicates that we are only able to detect place-of-residence employment effects larger than 0.22 and 0.45 for resident catch and local landings, respectively, with 95% confidence.For comparison, at the community level, we are able to detect place-of-residence employment effects larger than 0.058 and 0.068 for resident catch and local landings, respectively, with 95% confidence. Power analyses for wage effects reach similar conclusions. Thus, our analysis may not powered enough to detect meaningful place-of-residence and place-of-work effects at the borough level.

Table C.3: Indirect Impacts of Catch and Landings at Borough Level

	Resident Catch							
	Place-of-Residence				Place-of-Work			
	Wages		Employment		Wages		Employment	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Elasticity	0.028**	0.003	0.006	−0.004	0.019	0.036	−0.011	−0.007
	(0.011)	(0.007)	(0.008)	(0.016)	(0.020)	(0.029)	(0.012)	(0.062)
$\Delta Y/\$$	0.44	0.05	1.80	-1.19	0.23	0.43	-3.17	-1.94
95% CI	[0.09,0.79]	[-0.17,0.28]	[-3.5,7.1]	[-11.2,8.81]	[-0.24,0.7]	[-0.25,1.11]	[-10.15,3.81]	[-37.56,33.68]
First-stage F		89.43		89.43		89.43		89.43
N Places	25	25	25	25	25	25	25	25
Observations	327	327	327	327	327	327	327	327
	Local Landings							
Elasticity	0.001	−0.022	−0.011	−0.016	0.012	−0.137*	0.009	−0.143
	(0.006)	(0.015)	(0.010)	(0.021)	(0.017)	(0.073)	(0.015)	(0.122)
$\Delta Y/\$$	0.00	-0.09	-1.05	-1.46	0.04	-0.48	0.86	-13.21
95% CI	[-0.05,0.05]	[-0.21,0.03]	[-2.85,0.75]	[-5.34,2.42]	[-0.08,0.16]	[-0.99,0.03]	[-1.88,3.61]	[-35.42,9.01]
First-stage F		20.51		20.51		20.51		20.51
N Places	18	18	18	18	18	18	18	18
Observations	239	239	239	239	239	239	239	239
Place Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
van Dijk	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

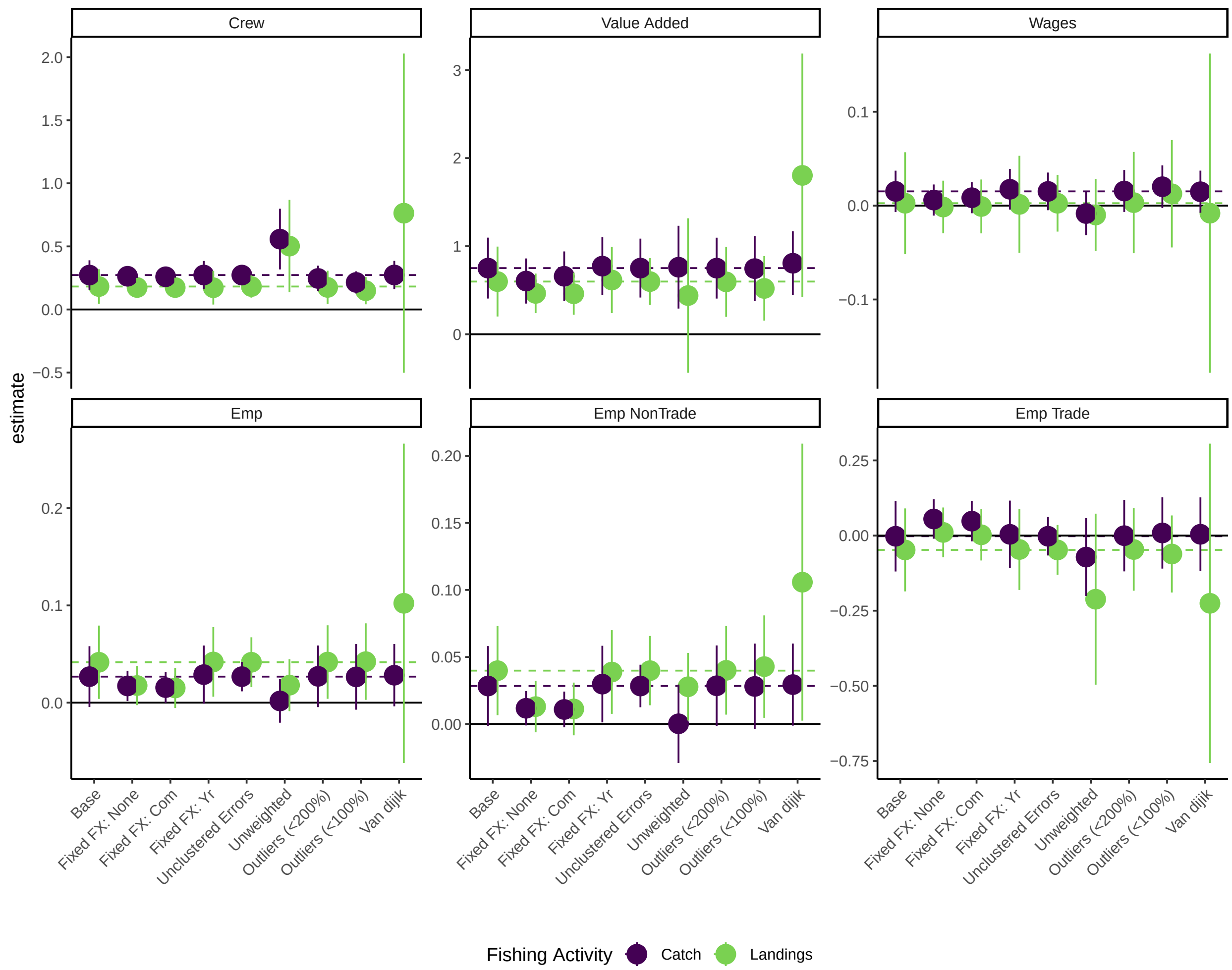
Note: *p<0.1; **p<0.05; ***p<0.01. Errors clustered at the borough level, however, number of clusters is less than conventional thresholds leading to underestimated standard errors. Unadjusted standard errors lead all results to be statistically insignificant estimates for all outcomes. Regressions weighted by average fishing activity by borough across time. Sample period is 2001-2015. Pre-sample period for IV construction is 1998-2000. van Dijk first-stage correction subtracts own-catch from fishery earnings in first-stage.

Appendix D Robustness and Instrument Validation

D.1 Robustness to Specification

Figure D.3 shows the robustness of the community level results (six outcomes) to a number of alternative specifications for both community catch and local landings. Alternative specification of fixed effects (none, community only, annual only), unclustered standard errors, unweighted regressions, dropping outlieres of annual changes in fishing activity larger than 200% or larger than 100%, and Van Dijk's 2018 leave-out-own correction to the instrument. Generally speaking, the results are qualitatively similar across these outcomes and specifications with two exceptions. The Van Dijk correction for landings reduces the first-stage fit of the instrument, thereby increasing the error in the second stage. Unweighted regressions also tend to reduce the first-stage fit, which is to be expected given that relatively more weight is now placed on communities with less systematic variation in fisheries activity. In turn, our second-stage estimates are less precise (particularly for local landings). Unweighted regressions strengthen the results for crew, but attenuate the effects on wages and employment.

Figure D.3: Robustness to Model Specification



Coefficient estimates and 95% confidence intervals for the base (preferred specification) and alternative specifications. Dashed lines are the level of the base specification for reference. The alternative specifications include: no fixed effects, community fixed effects only, year fixed effects only; unclustered errors; dropping outlier observations with very large changes in catch/landings or the instruments of such of either $> 100\%$ change or $> 200\%$ change; and use of the Van Dijk correction.

D.2 Falsification Test of Results

We adopt the spirit of the falsification test used by Autor et al. (2013) in their study of the effect of contemporaneous Chinese imports on contemporaneous US manufacturing employment. These variables are measured as decade-over-decade changes. As a falsification test for their findings (particularly for reverse causality), they test for the effect of *past* manufacturing employment on *current* Chinese imports. We conduct a similar falsification test (past outcomes regressed on current determinants) noting a few important distinctions in our exercise. Our analysis exploits year-to-year fluctuations, while Autor et al. (2013) uses decade-on-decade changes. Autor et al. (2013) also have a much longer time series (37 years compared to the 16 years in our analysis), which makes it easier for their test to argue for "sufficiently deep" lags. Finally, their falsification is motivated by the major structural changes to Chinese trade relations. In our setting, there is no obvious structural change that would provide an intuitive pre-exposure period, as people have fished Alaskan waters for millennia. With these distinctions noted, the falsification test we specify still provides some validation that we are correctly interpreting the causal direction of the effect we find.

Our main specification in Eq. 1 estimates the relationship between current economic outcomes and current fishing revenues, where both variables are measured as percent annual changes. Because of the three issues we note above, it is unclear how many lags are sufficient to qualify as a "pre-exposure" period. Because a pre-exposure period is unclear, we opt to test each possible lag of the economic outcome. We also test each lead order for good measure (this is a test of long run effects or persistence). The falsification specification takes the form

$$\Delta y_{ct-L} = \beta \Delta x_{ct} + \tau_t + \alpha_c + \epsilon_{ct},\ \forall L \in \{-14, -13, -12...12, 13, 14\}, \tag{D.1}$$

where Δy_{ct-L} is the year-over-year change in the logged outcome variable y, for community c, in year $t - L$, where L is a lag order going from -14:14. Δx_{ct} is the year-over-year change in logged fishing revenue generated by fishers residing in community c in year t. τ and α are year and community fixed effects, respectively. ϵ is the econometric error. Eq. 1 is estimated by 2SLS, where we instrument Δx_{ct} with the shift-share instrument described in the main text, Eq. 2.

We estimate the equation for each of the 28 lags and leads across eight outcome variables. These outcomes are: IRS AGI, total wages, employment, traded-sector employment, non-traded sector employment, new hires, crew licenses, and processor value added. When $L = 0$, the falsification-test specification is equivalent to the main specification in the text. We plot each of these results in Figure D.4 for resident catch and Figure D.5 for local landings. The vertical dashed line is $L = 0$, our main specification. Estimates of β and associated 95%

confidence intervals are plotted for each lag specification.

Our causal interpretation of current fishing activity leading to changes in current economic activity would be confounded if past economic activity caused current fisheries activity. Such endogeneity would be particularly evident in the figures if there were observable pre-trends or structure in the lead-up to the contemporaneous shock. The third panel of Figure D.4 plots the falsification test for the result we highlight in the abstract of the paper, that a \$1 increase in resident catch results in and increase of 1.54 in AGI for residents of the borough. Each of the 14 lags tested are statistically insignificant and smaller in magnitude than the true effect. In other words, we find no evidence that past AGI influences future instrumented catch earnings. We also find no compelling evidence that the effect is measured in the wrong period; as leads are small in magnitude and generally insignificant. Instead, we observe a strong break in the series at $L = 0$, the period of the contemporaneous shock. Similarly, we do not observe a pattern or trend in the lags for the other seven outcomes, with one possible exception: we find that at $L = -1$, there is a statistically significant negative relationship between crew labor and next period resident catch earnings. However, our contemporaneous result at $L = 0$ represents a strong deviation away from the relatively noisy trend in the lag and lead years.

Figure D.5 plots the local landings elasticities for the aforementioned eight outcomes. Again, we observe no trend leading into our significant findings for crew, employment, and non-traded sector employment. Looking at $L = 0$ for employment, for which we obtain statistically significant effects (particularly in the non-traded sector), our results represent a strong break away from the noisy trends in the data. No lag order has statistically significant effects for crew, employment, or non-traded sector employment.

Overall, these falsification results supports the causal interpretation of the effects we describe in the paper.

D.3 Instrument Validation

Borusyak et al. (2018) demonstrate two necessary conditions for shift-share instrument validity: (*i*) variation in the shift-share instrument cannot be driven by a finite set of industries (fisheries), and (*ii*) variation in the shift-share instrument must stem from a large number of independent shifts relative to the sample.

With respect to the first condition, we plot the cumulative density function (CDF) of each fishery's share of community earnings in D.6. Each panel contains the fisheries associated with a particular species, and each curve corresponds to a gear and area specification to describe a unique fishery (205 in total). The CDF describes the fraction of communities which have a given share of their fisheries revenue from that particular species. Most of the CDF curves have a distinct "hockey-stick" shape, indicating that many communities (e.g., greater than 75%) have fisheries that make up less than 25% of there revenue. In other words, a small hand-full of fisheries do not drive the earnings for most communities. In fact, in the most extreme case of portfolio concentration, only 10% of communities receive more than 50% of their total earnings from a single fishery (the halibut longline fishery for vessels under 60').

For the second condition, each of the shift instruments also display a considerable amount of variation and tend to be relatively uncorrelated with each other, as shown by plots of the coefficient of variation and pair-wise correlation coefficients between fisheries in Figure D.7. This is also true for the largest five fisheries in the state (by gross value).

To test the robustness of the instrument, we iteratively drop the 10 highest-value fisheries from the analysis to verify that no single fishery dominates the estimated effect. Fishery value is determined by the mean ex-vessel earnings in the sample time-frame. Table D.4 summarizes these fisheries and the changes to the first-stage regression from excluding them from the analysis. Figure D.8 shows the estimated β coefficients and associated 95% confidence intervals estimated after dropping a given fishery from the analysis.

Generally, the results are robust to dropping any of the top-10 fisheries from the analysis. First-stage coefficient estimates for resident catch and landings change only modestly from the full sample estimates, and first-stage F-statistics remain above the conventional

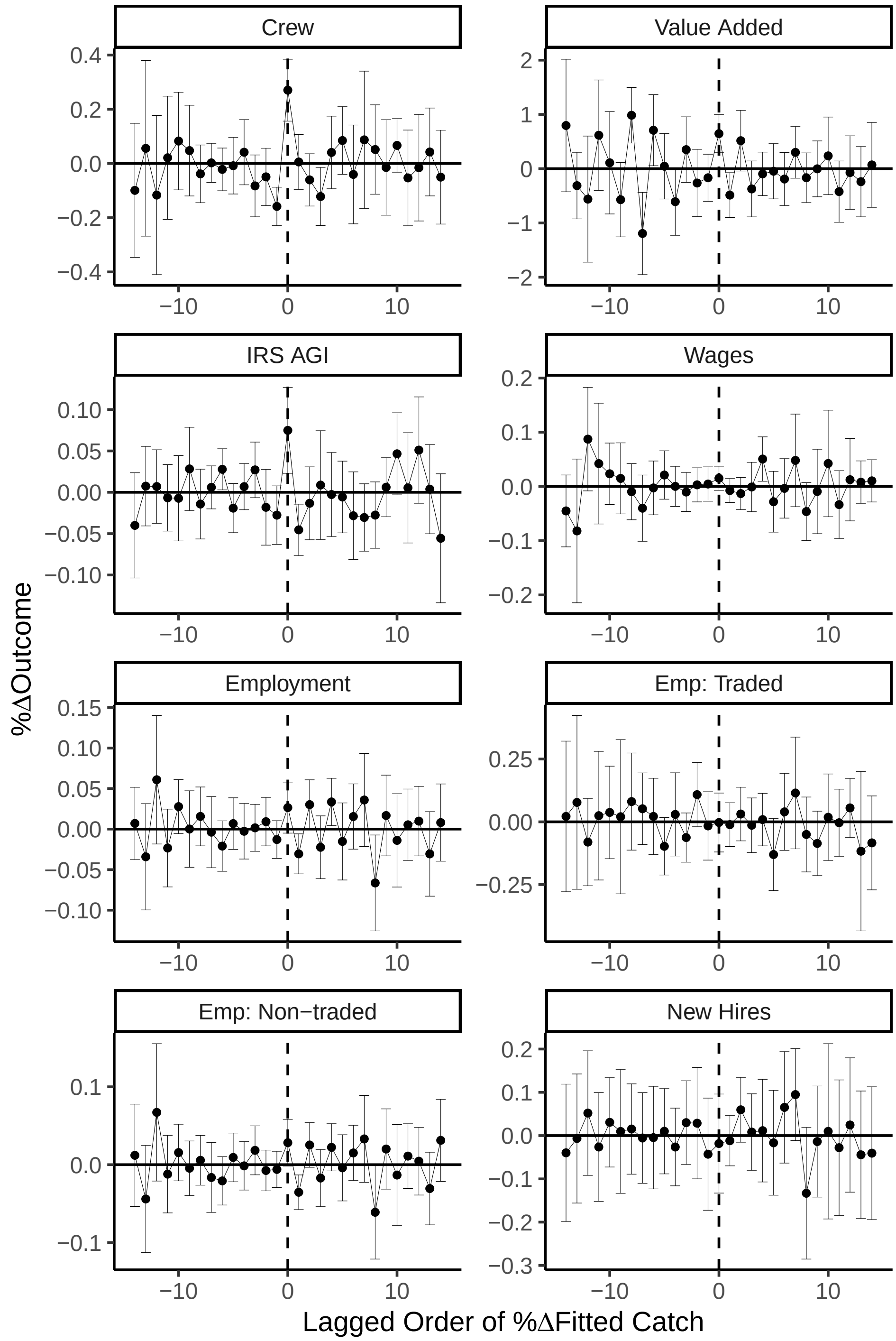
Table D.4: Robustness to Inclusion of Top-10 Fisheries by Value

Characteristics of Dropped Fishery				Catch			Landings		
Code	Description (Species, Gear, Area)	Mean Earnings ($m/y)	Mean Permits	# Places	1st Stage γ	F-stat	# Places	1st Stage γ	F-stat
None	Full Sample			200	0.75	107.73	69	0.63	16.22
B06B	Halibut, Longline <60', Statewide	122.80	2,202	196	0.80	100.09	68	0.64	14.86
S03T	Salmon, Driftnet, Bristol Bay	106.78	1,845	196	0.71	80.64	67	0.62	15.02
T91Q	Tanner Crab, Pots >60', Bering	90.35	134	200	0.76	110.28	69	0.64	15.93
S01A	Salmon, Seine, Southeast	61.25	375	200	0.77	105.81	69	0.60	15.41
B61B	Halibut, Longline >60', Statewide	53.29	249	200	0.74	115.31	68	0.64	17.16
C06B	Sablefish, Longline <60', Statewide	47.54	504	199	0.76	104.28	69	0.63	15.66
S03E	Salmon, Driftnet, PWS	38.69	537	199	0.76	156.89	69	0.67	26.28
S01E	Salmon, Purse Seine, PWS	36.81	263	200	0.75	70.47	69	0.57	11.94
S15B	Salmon, Power Troll, Statewide	29.55	962	200	0.74	102.48	69	0.64	15.90
S01K	Salmon, Seine, Kodiak	28.10	368	200	0.76	109.28	69	0.64	15.46

Code is the CFEC fishery identifier. Mean earnings are the average annual ex-vessal value of fish caught in the dropped fishery from 2000-2015. Mean pemits are the average number of permits over the same time period. # Places are the number of communities that remain in the sample after dropping a given fishery from the analysis. 1st Stage γ is the estimated coefficient value in the first stage, and F-stat is the associated first-stage F-stat value.

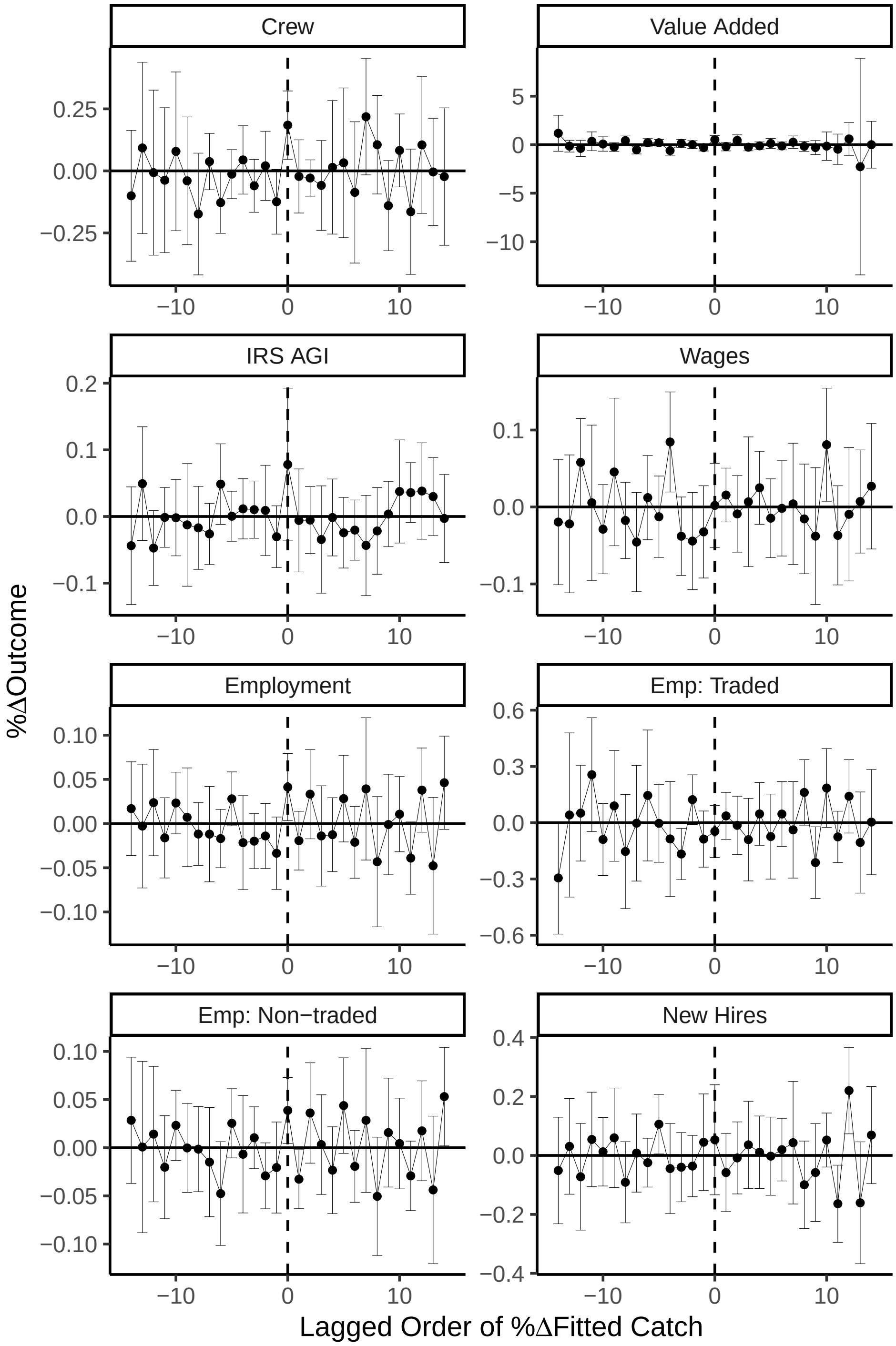
threshold level. In the second stage (Figure D.8), no inference for any outcome changes with respect to excluding a given species' resident catch from the analysis. For landings, excluding landings for S 03T, the Bristol Bay drift gillnet fishery, has a somewhat appreciable effect, as the employment change is statistically indistinguishable from zero with this fishery's local landings excluded.

Figure D.4: Falsification Test Using Outcome Lags and Leads, Resident Catch



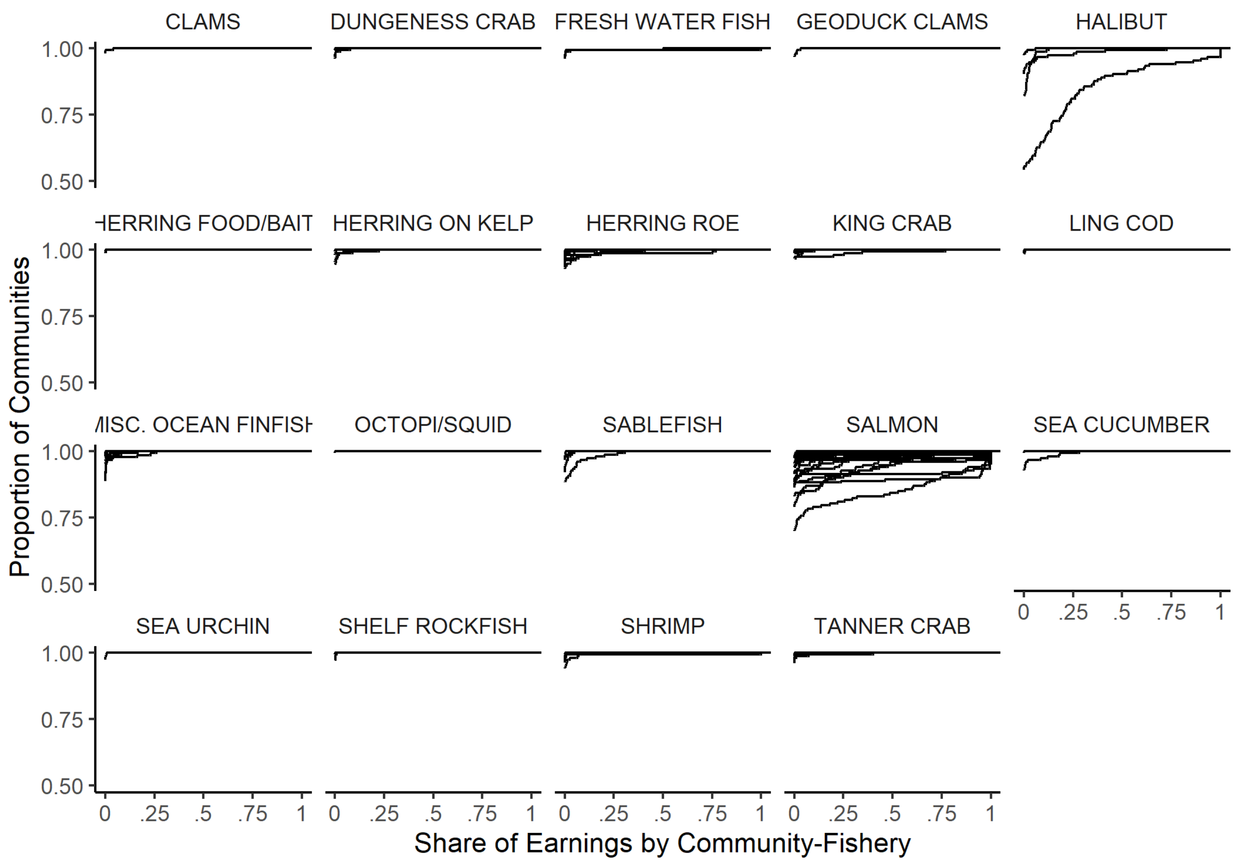
Coefficient (elasticities) and 95% confidence intervals estimated by Eq. D.1. The x-axis is the lag (lead) order of the specified outcome variable, -14:14. L=0 is equivalent to our main specification in Eq. 1. Each panel is one of 8 local economic outcomes measured at the lowest level of spatial aggregation where data are available. All are measured at the community level, except for IRS AGI which is measured at the borough level.

Figure D.5: Falsification Test Using Outcome Lags and Leads, Local Landings



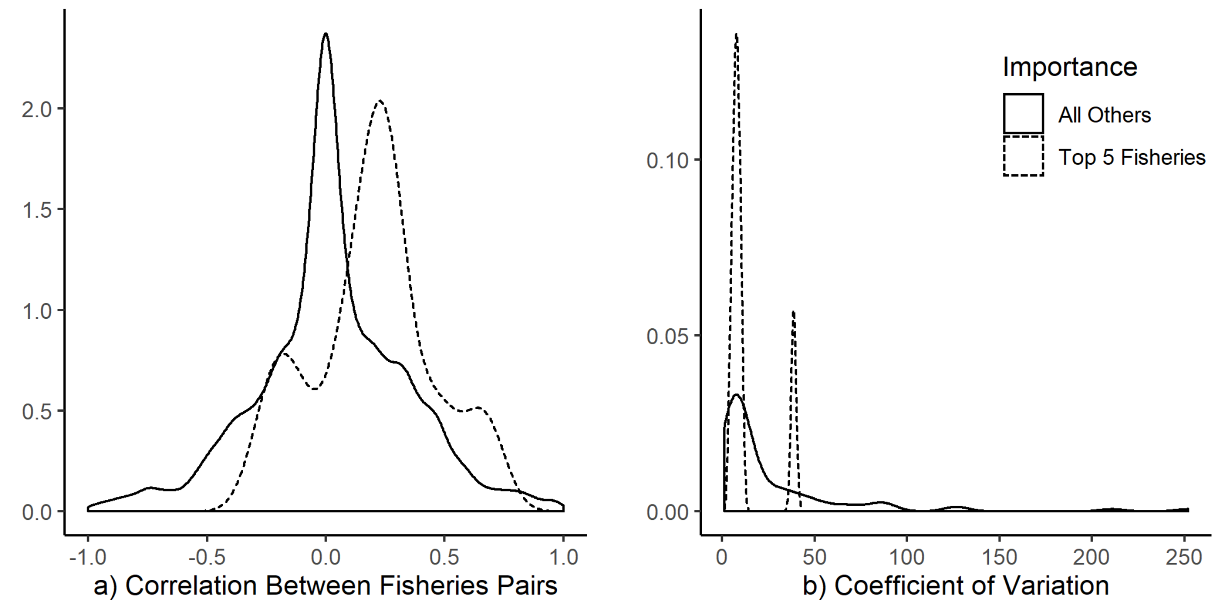
Coefficient (elasticities) and 95% confidence intervals estimated by Eq. D.1. The x-axis is the lag (lead) order of the specified outcome variable, -14:14. L=0 is equivalent to our main specification in Eq. 1. Each panel is one of 8 local economic outcomes measured at the lowest level of spatial aggregation where data are available. All are measured at the community level, except for IRS AGI which is measured at the borough level.

Figure D.6: Cumulative Density Functions, by species



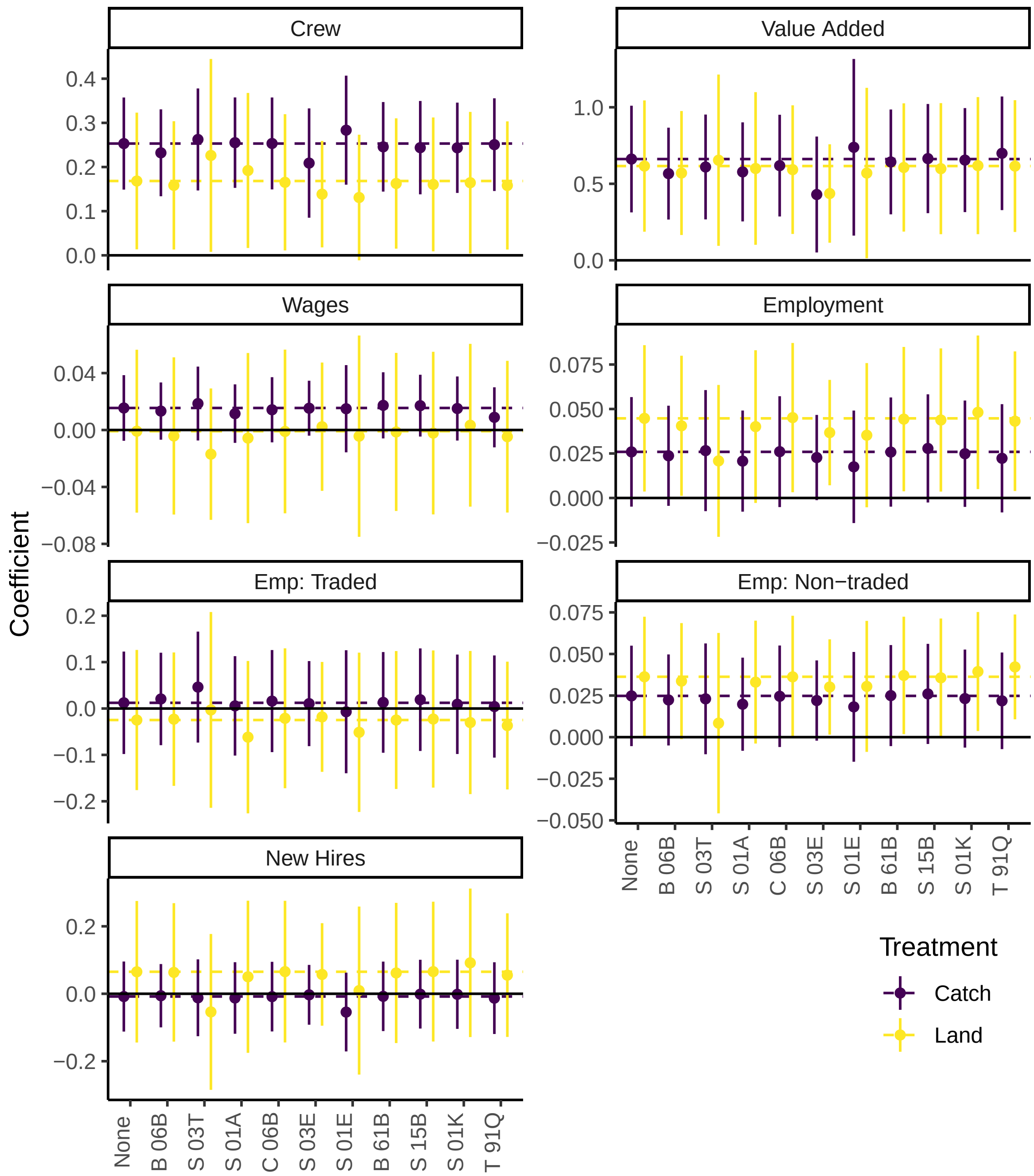
Are certain fisheries dominant in the portfolios of community fishery earnings? Each line plots the cumulative density function of a particular fishery's share of community fishery earnings, grouped by species of fish. The most extreme case is found for a particular halibut fishery (longline gear with vessels under 60'). Eighty-percent of communities receive less than 25% of their total earnings from this halibut fishery, and 90% of communities receive less than 50%.

Figure D.7: Density of correlation between fisheries and variation within fisheries



Panel a) plots the density of the correlation in annual earnings growth rates between each unique combination of fishery pairs. A majority of pairs have a correlation of less than 0.25, highlighting the independence between shocks to fisheries. The top five fisheries by value exhibit a similar pattern of low correlation between them and other fisheries, with 60% of these correlations below 0.25. Panel b) plots the density of the coefficient of variation (CV) of each fishery's annual earnings growth rates. The typical fishery shows a high degree of variation with a CV of 14. Among the top five fisheries, the CV ranges from 5.2 to 38.7, with a median CV of 8.1; these values are still quite large. Having highly variable and independent fisheries shocks provides validation for the shift-share instrument.

Figure D.8: Robustness to Inclusion of Top-10 Fisheries by Value



Coefficient (elasticities) and 95% confidence intervals estimated by Eq. 1. The x-axis denotes which of the top-10 fisheries (by mean annual value) is dropped from the sample (see Table D.4 for fishery code descriptions). Each panel is one of 7 local economic outcomes measured at the lowest level of spatial aggregation where data are available. All are measured at the community level. Dashed horizontal lines correspond to the estimated elasticity for the full sample.