The role of fisheries diversification in economic growth and stability: Evidence from Alaska's fishing economies

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Abstract

Climate change poses serious challenges to the growth and stability of fishing communities. While a diverse portfolio of fisheries has been shown to stabilize income for individual fishers and communities, evidence regarding its role in broader local economies remains limited. This study addresses this gap by examining how fisheries and industrial diversification shape economic growth and stability. Using a hyperbolic distance function (HDF), we analyze 17 years of fisheries and economic data for 177 Alaskan fishing communities. Our findings show that both fisheries and industrial diversification significantly affect employment growth and the stability of local fishing economies. Economic stability often comes at the cost of reduced growth, reflecting the risk-return trade-offs inherent in diversification. We also identify a complementary relationship between industrial diversification and fisheries specialization. This dual-track strategy, which balances diversification and specialization across fisheries and industrial sectors, enables communities to adapt their economic structures to local circumstances while minimizing trade-offs between growth and stability. These results suggest that policymakers should prioritize strategies that foster balanced diversification and specialization, tailored to community conditions, to strengthen resilience in the face of climate-related uncertainties.

Keywords: Fisheries diversification; Industrial diversification; Economic growth and instability; Climate resilience; Hyperbolic distance function; Stochastic frontier analysis; Alaska.

1 Introduction

Climate-induced changes in the ocean increasingly threaten the sustainability of coastal communities that rely on fisheries. Shifts in the distribution and productivity of fish stocks compound existing pressures from overexploitation, sea level rise, ocean acidification, and the globalization of the seafood trade (Anderson et al., 2018; Pinsky et al., 2018; Free et al., 2019; Rogers et al., 2019). These challenges are particularly acute in vulnerable communities, where declining and aging populations exacerbate risks of economic and social instability (Himes-Cornell and Kasperski, 2015; Colburn et al., 2016; Blasiak et al., 2017). As traditional fishing practices face growing uncertainties, the resilience of these communities depends on their ability to adapt to changing coastal, demographic, and economic conditions (Birkenbach et al., 2023).

Diversifying fishing activities across multiple fisheries is a promising strategy for coastal communities to adapt to the uncertainties of a changing marine environment. Just as a diversified portfolio of financial assets reduces overall return variability (Markowitz, 1952), a well-diversified portfolio of fisheries revenue streams can lower a community's exposure to climate-induced shocks, particularly when shocks affect fish populations and markets asynchronously. Extensive research supports this stabilizing effect, showing that diversification can buffer fluctuations in commercial fisheries and the livelihoods they support (Kasperski and Holland, 2013; Sethi et al., 2014; Holland et al., 2017; Young et al., 2019; Fisher et al., 2021; Abbott et al., 2023). Consequently, many studies emphasize harvesting diverse fisheries and adapting portfolios to changing conditions as a critical means of stabilizing local economies that depend on fisheries (Cline et al., 2017; Bris et al., 2018; Salgueiro-Otero et al., 2022).

While diversifying fisheries portfolios can support adaptation, it entails notable challenges. Most fisheries are not open-access and require fishers to purchase permits, which can be prohibitively expensive (Holland and Kasperski, 2016). Limited access to capital further constrains fishers' ability to invest in permits and expand fishing opportunities (Olson, 2011). Diversification may also dilute the knowledge and efficiencies gained through specialization, potentially reducing overall returns (Anderson et al., 2017). Geographic and ecological constraints matter as well: in regions with fewer or more volatile local fisheries, communities have limited options for constructing a diversified portfolio, leaving them less able to capture diversification benefits (Sethi et al., 2014; Young et al., 2019). In addition, as fisheries management has become more prescriptive to address overfishing and overcapacity, the scope for diversifying across fisheries has narrowed, and diversification has declined in many parts of the world (Holland et al., 2017; Abbott et al., 2023).

An important uncertainty in assessing the buffering role of fisheries diversification concerns the position of commercial fishing within the broader local economy. In many regions, the economic prominence of commercial fishing is declining as coastal communities face increasing competition for limited offshore space from aquaculture, tourism, offshore wind energy, and resource extraction (FAO, 2024). Future resilience will likely hinge on communities' ability to adapt to a shifting economic landscape shaped by emerging marine industries. Just as fisheries diversification can stabilize fishing revenues, industrial diversification can provide broader economic stability by offsetting losses in one sector with gains in others (Chandra, 2002, 2003; Kluge, 2018; Hafner, 2019). Diversifying across sectors reduces reliance on fisheries and mitigates exposure to fluctuations in fish populations and seafood markets. Communities that successfully diversify their economies and adjust industrial portfolios toward emerging marine sectors are therefore more likely to achieve greater economic stability and growth (van Putten et al., 2016).

Empirical evidence on the roles of fisheries and industrial diversification in the stability and growth of local fishing economies remains limited. Prior research has largely examined the stabilizing effect of fisheries diversification on fishing revenues, with less attention to local economic outcomes such as employment or wages (Sethi et al., 2014; Cline et al., 2017; Young et al., 2019; Fisher et al., 2021). Moreover, many studies emphasize reduced instability while overlooking implications for returns or growth, despite the well-established trade-off between stability and growth in modern portfolio theory (Markowitz, 1952). Examining the joint dynamics of economic growth, instability, and diversification is therefore essential for a holistic understanding of these trade-offs in coastal economies and for informing policies that support adaptation to a changing marine environment.

In this study, we examine how fisheries and industrial diversification contribute to long-term growth and stability in local fishing economies. We focus on Alaska's fishing communities, which accounted for 60% of U.S. domestic seafood landings in 2020 (NOAA, 2022). These communities face significant climate-related challenges, including warming ocean temperatures, ocean acidification, shifting fish-stock distributions, and increased price volatility (Himes-Cornell and Hoelting, 2015; Kasperski and Holland, 2013). Using 17 years of employment and fishing revenue data from 177 communities, we estimate the trade-off between employment growth and stability with a hyperbolic distance function (HDF) adapted from production economics. The HDF identifies the frontier of efficient combinations of employment growth and stability and, in turn, allows us to characterize how fisheries and industrial diversification shape efficient growth–stability outcomes. This framework provides new insight into the growth–stability relationship and the interaction between fisheries and industrial diversification in fishing communities.

Our findings show that both fisheries and industrial diversification significantly shape employment growth and stability. Economic stability often comes at the cost of lower growth, reflecting the risk–return trade-offs inherent in diversification. We also identify a complementary relationship between industrial diversification and fisheries specialization. A dual-track strategy that balances specialization and diversification across fisheries and industrial sectors enables communities to adapt their economic structures to local circumstances while minimizing growth–stability trade-offs. Our results suggest that policymakers should prioritize strategies that foster balanced diversification and specialization across fisheries and industrial sectors to build resilience in fishing communities facing climate-related uncertainties.

2 Empirical setting and data

Alaska offers a valuable context for studying how fisheries and industrial diversification shape local economic growth and stability. The state's commercial fishing sector is substantial, generating \$5.2 billion in wholesale revenues in 2022 and employing 48,000 workers, representing 66% of manufacturing jobs (ASMI, 2024). Its economic impact is significant: a 10% increase in fishery earnings raises resident income by 0.7% (i.e., \$1.54 per additional dollar earned) (Watson et al., 2021). At the same time, Alaska's economy is not solely dependent on fishing. Since the 1980s, the oil and gas sector has been dominant, and tourism, shipping, transportation, and the public sector also play vital roles. These industries often surpass fishing as primary sources of employment in coastal communities, underscoring the importance of industrial diversification for local economies.

Alaska is also a compelling case study because unique data measure employment and wages by workers' place of residence. Traditional datasets, such as the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), typically report employment and wage statistics by place of work and at aggregated geographies such as the county. This approach presents two challenges. First, county-level statistics can obscure meaningful empirical relationships, particularly in regions like Alaska and the Western U.S., where counties are geographically large and encompass heterogeneous communities. Second, discrepancies between where individuals live and work complicate inferences about people rather than places (Guettabi and James, 2020; Jacobsen et al., 2023).

The Alaska Local and Regional Information (ALARI) database addresses these challenges by reporting employment and wage data by industrial sector measured at workers' places of residence. This approach is enabled by the Alaska Department of Labor and Workforce Development's (AKDOL) linkage of unemployment insurance records (also used in the QCEW) with Alaska's Permanent Fund Dividend (PFD) application data. The PFD, paid annually to eligible residents who have lived in the state for a full calendar year and intend to remain indefinitely, includes applicants' residential addresses. This linkage provides granular, community-level insight into employment and wage patterns and offers a basis for examining how fisheries and industrial diversification relate to local economic growth and stability.

We compile a comprehensive dataset of economic and commercial fishing variables for all Alaskan communities involved in commercial fisheries between 2000 and 2016. Data on permit-owner earnings are sourced from the Alaska Commercial Fisheries Entry Commission (CFEC) Basic Information Tables, which provide annual records of harvests and earnings for each community–fishery pair. Alaskan fisheries are defined by species, fishing district, and gear type, and participation requires a fishery-specific permit issued by the CFEC. In 2010, 20,275 permits were issued across 205 fisheries in Alaska, with permit-owner communities identified by the addresses listed on their permits. The value of deliveries to local processors is aggregated from individual delivery records reported through the Alaska Department of Fish and Game's (ADF&G) fish tickets and eLandings systems.

Information on local wages and employment comes from the ALARI database, which provides sector-specific economic data for 344 Alaskan communities over the same period. Complementing these data, demographic variables, such as average population size, were obtained from the Alaska Bureau of Labor Statistics to give broader context to the local economies of fishing communities. For our analysis, we focus on 177 communities that consistently engaged in commercial fishing throughout the study period (2000-2016), covering a period of 17 years.

It is important to clarify that ALARI records are derived from unemployment insurance data, which exclude many categories of workers in the seafood industry. Commercial fishers and crew, who are typically self-employed or contract workers, are not captured. Wages for upstream and downstream proprietors and other self-employed individuals are also omitted. By contrast, wage and employment data for workers employed by commercial processors are included in ALARI. This distinction is crucial for interpreting which types of employment are affected by fisheries and industrial diversification. Accordingly, we do not consider the direct effect of fisheries diversification on fisheries employment.

A further consideration is that ALARI measures the number of individual workers rather than full-time equivalent (FTE) jobs. Because Alaska's seafood industry is highly seasonal, many workers are employed only for a few months each year. Our employment estimates may therefore differ from studies that report FTE measures.

3 Diversification, growth, and growth instability in Alaskan communities

In this study, we use employment growth rather than GDP to measure economic growth because employment data are available at a finer resolution (both geographically and by industry), whereas GDP is typically reported only at broader geographies (e.g., state). Employment metrics therefore provide more detailed micro-level insights into local fishing economies and align with our focus on industrial diversification, as sector-level job trends capture economic shifts more consistently. We measure a community's average economic growth using the geometric growth return of employment, which captures compounding (as with compound interest) and provides a more accurate view of long-run outcomes. Following Lande (1994), Chandra (2002), and Hafner (2019), this measure is obtained by estimating: [1]

$$\log(Emp_{t,c}) = \beta_{0,c} + \beta_{1,c} \cdot t + \epsilon_{t,c}, \tag{1}$$

where $Emp_{t,c}$ is employment in community c at year t, and $\beta_{1,c}$ denotes the instantaneous employment growth rate for community c. We convert this to an average annual geometric growth return, $1 + \mu_c = \exp\{\beta_{1,c}\}$, where μ_c is community c's geometric growth rate. Economic instability is quantified as the standard deviation of the residuals from the ordinary least squares (OLS) estimate of the log-linear time trend in Equation (1). The fitted trend captures the long-run (geometric) return. Larger positive or negative deviations from this trend are interpreted as instability in year-to-year growth. Further details and justification are provided in Appendix B.

Previous studies commonly measure diversification using the inverse Herfindahl–Hirschman Index (HHI) or the Shannon diversity index (Kasperski and Holland, 2013; Holland and Kasperski, 2016; Sethi et al., 2014; Kluge, 2018; Hafner, 2019). We adopt the Shannon diversity index, defined as the exponential of Shannon entropy, to quantify industrial diversification. This measure has intuitive interpretation: if a community achieves the same level of economic growth across N industrial sectors and then doubles the number to $2N$ while maintaining the same growth, the index also doubles. It represents the effective number of perfectly

[1] This approach is also employed in reports by the World Bank (Chandra, 2002).

balanced sectors within a community (Jost, 2006; Abbott et al., 2023).

We calculate this index from employment *growth* across 13 industrial sectors within a community, rather than from employment levels.[2] Formally,

$$Div_c = \frac{1}{T}\sum_{t=1}^{T} \exp\left(-\sum_{i=1}^{N} P_{ict} \, \ln P_{ict} \right), \tag{2}$$

$$P_{ict} = \frac{|\Delta Emp_{ict}|}{\sum_{j=1}^{N} |\Delta Emp_{jct}|}, \tag{3}$$

where P_{ict} is the share of total employment growth contributed by sector i in community c in year t, and ΔEmp_{ict} is sector-i employment growth. The Shannon-based diversification measure in Equation (2) equals the exponential of Shannon entropy evaluated on $\{P_{ict}\}_{i=1}^{N}$. It approaches 1 when a single sector dominates and increases with diversification; Div_c averages this annual index over the T years.

Kluge (2018) advocates growth-based diversification measures over traditional size-based measures (i.e., shares). Size-based indices can misleadingly encourage regions dominant in stable sectors to diversify into more volatile ones, potentially reducing stability rather than enhancing it; they also fail to distinguish how positive versus negative growth affects stability. As a result, size-based measures may mask underlying instability during periods of rapid sector-specific expansion or contraction, even when the industrial composition appears unchanged. A growth-based approach more accurately captures variability in sector contributions and provides a more reliable indicator of economic stability.

For fisheries diversification, we follow Sethi et al. (2014) and compute a Shannon diversity index based on fishing permits. Although many studies use realized fishing revenues or landings, those metrics are distorted by stochastic catch variation and price volatility. Using the number of active permits provides a more stable, ex-ante measure of diversification that avoids noise from short-run fluctuations in catch volumes and market conditions.

Table 1 reports summary statistics for the variables used in this study, calculated as averages over the study period. Long-run economic growth, measured by the average annual geometric return of employment in local fishing economies, is close to one, indicating near-zero growth. On average, employment in Alaska's fishing communities was largely stable or slightly declining, with an annual decrease of approximately 0.3%.

Industrial diversification averages 5.7 effective, perfectly balanced sectors based on the North American

[2] Our local fishing economy data classify industrial sectors using North American Industry Classification System (NAICS) codes, which are also used for federal and state labor statistics.

Table 1: Summary statistics

Variable	N	Mean	SD	Min	Max
Employment Growth (Return)	177	0.997	0.019	0.919	1.060
Growth Instability	177	1.080	0.062	1.008	1.387
Industrial Diversification	177	5.747	1.881	1.354	8.996
Fisheries Diversification	177	3.601	3.596	1.000	19.962
Population (Individuals)	177	2,908	21,457	13	282,781
Wage per Capita (USD)	177	9,998	4,313	1,325	27,362
Fishing Permit Share within Borough	177	0.151	0.246	0.002	1.000
Fishing Earnings to Wage Income Ratio	177	0.397	0.955	0.000	7.998

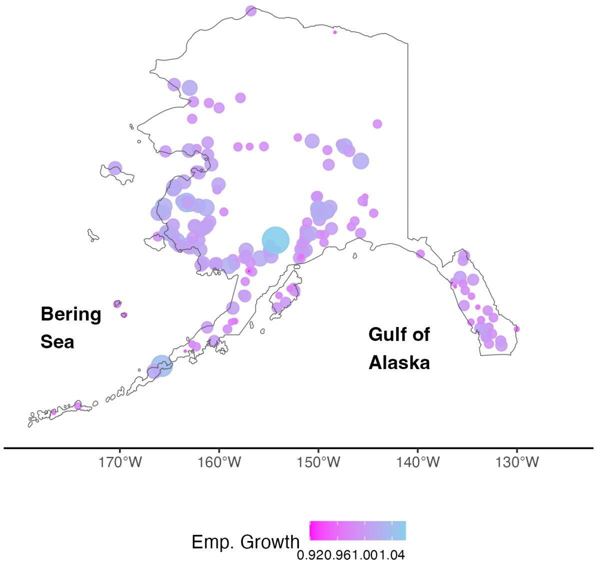
Notes: All values are averages over the study period.

Industry Classification System (NAICS). Fisheries diversification indicates typical engagement in 3–4 distinct fisheries per community, with notable heterogeneity across communities.

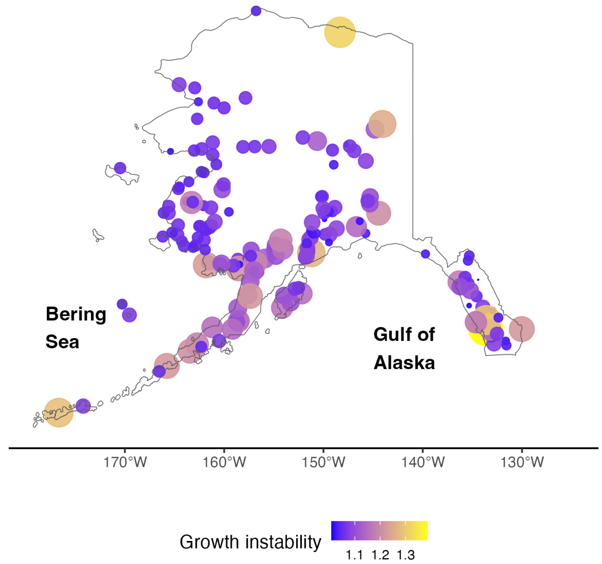
Population size across Alaskan fishing communities is highly dispersed, ranging from small settlements such as Ugashik (roughly a dozen residents on average) to Anchorage, the largest population center. This dispersion suggests that most fishing communities are moderately to sparsely populated. Fishing permit shares (a measure of spatial fisheries concentration within a borough) indicate that most communities are not dominant fishing hubs, whereas a few—including Sitka, Yakutat, Anchorage, and Juneau—emerge as hotspots with concentrated permits. The fishing earnings-to-wage income ratio, a measure of fishing dependency, points to moderate reliance on fishing: on average, revenue from the sector accounts for about 40% of total wage income from other industries, although dependence varies substantially, as reflected by the high standard deviation.

Figure 1 presents spatial patterns and relationships among the main variables. Alaska's fishing communities are generally concentrated along the coast in the Southwest, Southcentral (around the Gulf of Alaska), and Southeast regions, with some inland communities along the Yukon River primarily for salmon fisheries. Over the study period, employment growth was relatively steady overall, with higher growth in the Southwest than elsewhere. In Southcentral, communities with higher instability are primarily along the Gulf of Alaska, and these areas overlap with higher economic growth; however, in general, high growth does not strongly coincide with high instability.

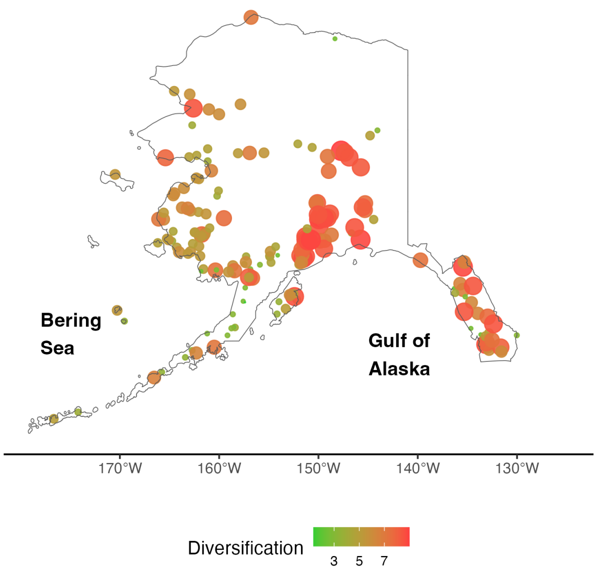
Industrial and fisheries diversification are positively correlated across communities. Communities in



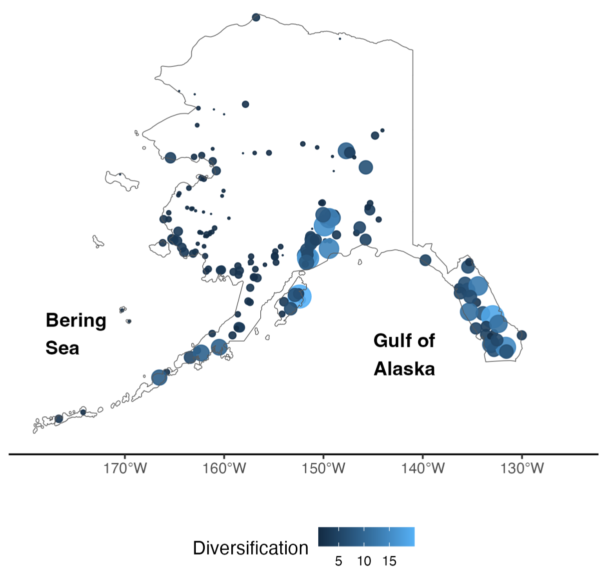
(a) Employment Growth Return



(b) Growth Instability



(c) Industrial Diversification

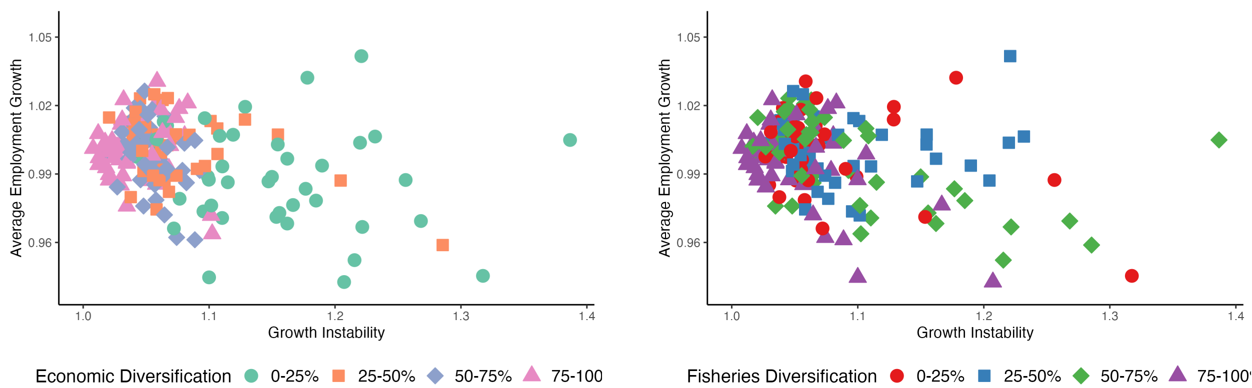


(d) Fisheries Diversification

Figure 1: Employment Growth, Instability, Industrial and Fisheries Diversification in Alaskan Fishing Communities (2000-2016)

Western Alaska display low diversification in both industrial structure and fisheries yet are associated with higher economic growth. This pattern suggests that more specialized regions (e.g., the Southwest) may be driving growth. Finally, the relationship between diversification (both industrial and fisheries) and economic instability is less distinct but generally negative. Communities along the Aleutian Islands (Bering Sea) and in Southeast with less diversification exhibit higher instability, consistent with the high-risk, high-return implication of modern portfolio theory.

Figure 2 provides a closer look at the relationship between employment growth return, economic growth instability, and diversification (industrial or fisheries). By plotting economic instability on the x-axis, employment growth on the y-axis, and coloring each fishing community by diversification quantile (in 4 groups, from low to high), we further examine their relationship in detail.



(a) By industrial diversification quantiles

(b) By fisheries diversification quantiles

Figure 2: Economic growth–instability portfolio profiles of Alaskan fishing communities by diversification quantiles (2000–2016). Colors and shapes of dots represent industrial and fisheries diversification quantiles (1st–4th).

In the left panel of Figure 2, the growth-instability portfolio for fishing communities is shown by industrial diversification. The figure provides a couple of insights: First, the distribution of the fishing communities' risk-return portfolio appears to form a general minimum-variance frontier as suggested by MPT. This indicates that the relationship between economic growth, as measured by employment in Alaska fishing communities, and the associated economic instability is inherently non-linear.

Previous research has analyzed risk and return in fishing revenue, typically focusing on the risk-diversification relationship using linear risk measures like the Coefficient of Variation (CV) of fishing revenue (Sethi et al., 2014; Kasperski and Holland, 2013; Abbott et al., 2023; Gokhale et al., 2024). However, if a non-linear relationship between economic growth and instability exists, a linear approach may fail to capture the true dynamics of risk-return-diversification. To address this limitation, our estimation approach (described below) relaxes the linearity assumption and employs a more flexible functional form to better understand the nuanced relationship between a community's economic growth and instability.

Second, the figure illustrates that fishing communities with higher industrial diversification (i.e., 3rd (50-

75%) and 4th quantiles (75-100%)) tend to cluster near zero growth (i.e., close to one as return) but with lower instability. This indicates that communities with greater industrial diversification may, on average, experience a steady-state employment growth status. Conversely, communities with low industrial diversification, particularly those in the first and second industrial diversity quantiles, exhibit greater dispersion in the growth-instability space.

4 A hyperbolic distance function approach

We adopt the hyperbolic distance production function (HDF) approach, commonly used in production economics. In this framework, economic growth is treated as a desirable output, while economic risk is considered an undesirable output in the growth process of communities. Here, x represents a vector of K inputs ($x \in \mathbb{R}_+^K$), y denotes a vector of V desirable outputs ($y \in \mathbb{R}_+^V$), and s refers to a vector of U undesirable outputs ($s \in \mathbb{R}_+^U$), produced as byproducts of y. The production technology is defined by the production possibility set:

$$T = \{(x, y, s) : x \in \mathbb{R}_+^K, y \in \mathbb{R}_+^V, s \in \mathbb{R}_+^U, x \text{ can produce } (y, s)\}. \tag{4}$$

The production technology is also characterized by a distance function, which provides insights into production dynamics by analyzing three key relationships: (1) the shape of the production frontier, including the curvature between outputs ($y - y'$ for desirable outputs and $y - s$ for desirable and undesirable outputs); (2) the relationship between inputs and outputs ($y - x$), analogous to a production function; and (3) the complementarity or substitutability between inputs ($x - x'$), such as the marginal rate of technological substitution (MRTS) along the isoquant (Morrison-Paul et al., 2000; Cuesta et al., 2009; Dalheimer et al., 2024). This approach offers a comprehensive framework for studying growth and stability dynamics in fishing communities, considering diversification and other community-specific factors.

The traditional output distance function measures the maximum feasible expansion of only desirable outputs (y) required to reach the boundary of the production possibility set (T). It evaluates the efficiency of a production bundle relative to the production frontier, defined as:

$$D^O(x, y, s) = \inf_\theta\{\theta > 0 : (x, \frac{y}{\theta}, s) \in T\}. \tag{5}$$

When $D^O = 1$, the production bundle is efficient and lies on the frontier. Conversely, $D^O < 1$ indicates

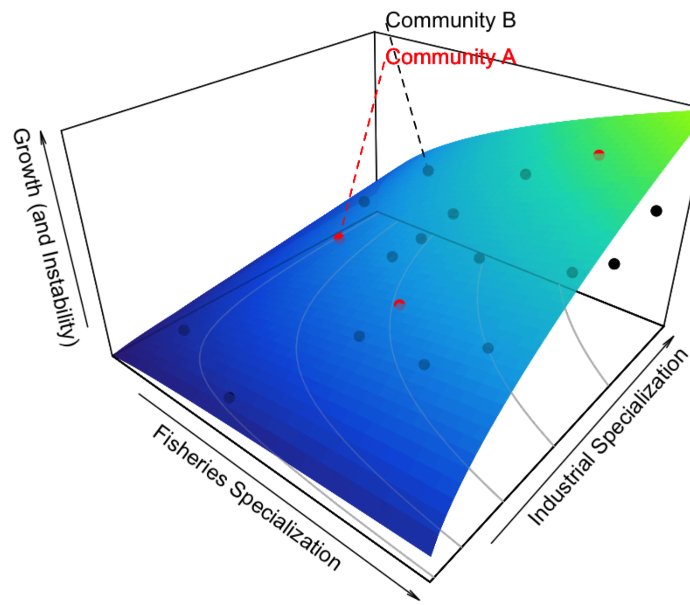


Figure 3: Conceptualized hyperbolic distance function characterizes the production possibility frontier between economic outputs and specialization (inverse diversification). Red dots (like Community A) represent communities that lie on the frontier—indicating fully efficient economic growth (appropriate growth and instability) at a given specialization level—while black dots (like Community B) indicate communities with room for further improvement with either more growth or less instability at given specialization.

inefficiency, suggesting that expanding desirable outputs (y) can bring the production bundle closer to the frontier. However, this function does not differentiate between desirable and undesirable outputs, limiting its capacity to address trade-offs between these two types of outputs effectively.

To overcome this limitation, the hyperbolic distance function (HDF) is introduced. The HDF allows for simultaneous adjustment of desirable and undesirable outputs, enabling a more nuanced measurement of production efficiency. By capturing both economic growth and instability as desirable and undesirable outputs, respectively, in our context, the HDF provides a comprehensive framework for evaluating the economic growth process in fishing communities. The HDF is defined as:

$$D^H(x, y, s) = \inf_\theta\{\theta > 0 : (x, \frac{y}{\theta}, \theta s) \in T\}, \tag{6}$$

where the HDF takes values between 0 and 1 (i.e., $D^H \in [0, 1]$). This function satisfies the following properties: (1) non-decreasing in desirable outputs, $D^H(x, \kappa y, s) \leqslant D^H(x, y, s)$ for $\kappa \in [0, 1]$; (2) non-increasing in undesirable outputs, $D^H(x, y, \kappa s) \leqslant D^H(x, y, s)$ for $\kappa \geqslant 1$; (3) non-increasing in inputs, $D^H(\kappa x, y, s) \leqslant$

$D^H(x, y, s)$ for $\kappa \geqslant 1$; and (4) almost homogeneity conditions, $D^H(x, \kappa y, \kappa^{-1}s) = \kappa D^H(x, y, s)$ (Cuesta et al., 2009). Using a flexible translog function, the HDF for the economic production process of community c can be specified as:

$$\begin{aligned}\ln D_c^H(x, y, s) = \alpha_0 &+ \sum_{k=1}^{K} \alpha_k \ln x_{k,c} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ln x_{k,c} \ln x_{l,c} + \sum_{v=1}^{V} \beta_v \ln y_{v,c} + \frac{1}{2}\sum_{v=1}^{V}\sum_{l=1}^{V} \beta_{vl} \ln y_{v,c} \ln y_{l,c} \\ &+ \sum_{u=1}^{U} \delta_u \ln s_{u,c} + \frac{1}{2}\sum_{u=1}^{U}\sum_{l=1}^{U} \delta_{ul} \ln s_{u,c} \ln s_{l,c} + \sum_{k=1}^{K}\sum_{v=1}^{V} \gamma_{kv} \ln x_{k,c} \ln y_{v,c} + \sum_{k=1}^{K}\sum_{u=1}^{U} \eta_{ku} \ln x_{k,c} \ln s_{u,c} \\ &+ \sum_{v=1}^{V}\sum_{u=1}^{U} \theta_{vu} \ln y_{v,c} \ln s_{u,c},\end{aligned} \tag{7}$$

Suppose a function F satisfies almost homogeneity of degree (k_1, k_2, k_3, k_4), then F satisfies the following condition:

$$k_1 \sum_{k=1}^{K} \frac{\partial F}{\partial x_k} + k_2 \sum_{v=1}^{V} \frac{\partial F}{\partial y_v} + k_3 \sum_{u=1}^{U} \frac{\partial F}{\partial s_u} = k_4 F \tag{8}$$

Since the hyperbolic distance function must satisfy almost homogeneity of degree $(0, 1, -1, 1)$, and using the partial derivatives derived in Equation (7), the following condition should be satisfied for the HDF:

$$\sum_{v=1}^{V} \frac{\partial \ln D^H}{\partial \ln y_v} - \sum_{u=1}^{U} \frac{\partial \ln D^H}{\partial \ln s_u} = 1. \tag{9}$$

To impose the homogeneity condition, we normalize the HDF by imposing the almost homogeneity condition, $D^H(x, \kappa y, \kappa^{-1}s) = \kappa D^H(x, y, s)$. Suppose $\kappa = \frac{1}{y_1}$, with y_1 being the first desirable output in the output vector y. The hyperbolic distance function then satisfies the following equation:

$$D^H(x, \frac{y}{y_1}, s \cdot y_1) = \frac{D^H(x, y, s)}{y_1}, \tag{10}$$

By taking the natural log on both sides,

$$\ln D_c^H(x, y^*, s^*) = \ln D_c^H(x, y, s) - \ln y_1, \tag{11}$$

where $y^* = y/y_1$ and $s^* = s \cdot y_1$. These values are plugged into Equation (7) to replace y and s. Thus, let $\ln D_c^H(x, y^*, s^*) = TL(x, y^*, s^*)$, where $TL(\cdot)$ is the translog hyperbolic distance function defined in

Equation (7). Furthermore, $\ln D_c^H$ is a one-sided community inefficiency component for each community c in economic production, rearranged as $\ln D_c^H = -u_c$ (Brümmer et al., 2002; Cuesta and Zofío, 2005; Cuesta et al., 2009). By rearranging the above equation with additional noise from estimation, we derive the estimation equation as follows:

$$-\ln y_1 = TL(x, y^*, s^*) + v_c + u_c, \tag{12}$$

where v_c is estimation noise that is normally distributed around zero, capturing all unobserved factors beyond the control of each fishing community in the economic production process. u_c represents the distance between the observed output vector and the boundary of the production possibility set. We assume u_c to be half-normally distributed around zero, as is common in the literature with this approach (Cuesta and Zofío, 2005; Cuesta et al., 2009; Zhang and Ye, 2015). Additionally, we allow u_c to be heteroskedastic as a function of community-specific characteristics (but not direct growth-relevant inputs), following Dalheimer et al. (2024) and Peña et al. (2018). To avoid the bias associated with the traditional two-step estimation process, where the frontier and inefficiency equations are estimated separately, we opt for the simultaneous estimation of the efficient frontier and inefficiency equations using maximum likelihood estimation (MLE), as outlined by Belotti et al. (2013) (Kluge, 2018; Wang and Schmidt, 2002; Belotti et al., 2013).

Post-estimation, following the procedure of Reimer et al. (2017) and Cuesta et al. (2009), with the estimated parameters and technical efficiency, we are able to compute the marginal rate of transformation (MRT) between undesirable and desirable outputs from the production, which represents the opportunity cost of reducing bad output concerning the forgone good output. The MRT is computed as a ratio of the first derivatives of the HDF with respect to desirable output y (here, employment growth) and undesirable output s (here, growth instability) as follows:

$$MRT_{s,y} = \frac{\partial s}{\partial y} = -\frac{\partial D^H/\partial y}{\partial D^H/\partial s} = -\frac{\varepsilon_{D,y}}{\varepsilon_{D,s}} \cdot \frac{s}{y}, \tag{13}$$

where $\varepsilon_{D,y}$ and $\varepsilon_{D,s}$ are distance function elasticities for y and s, estimated by differentiating the translog distance function.

The MRT can be challenging to interpret directly, as it depends on the specific output ratio. To clarify the trade-off in relative terms, independent of absolute output scales, Morrison-Paul et al. (2000) and Cuesta et al. (2009) suggest normalizing the MRT by the output ratio, s/y. Following this approach, we compute the normalized MRT (NMRT), which provides insights into the relative economic growth-risk relationship in Alaskan fishing communities, independent of output scale. The NMRT is expressed as $\text{NMRT}_{s,y} = -\frac{\varepsilon_{D,y}}{\varepsilon_{D,s}}$, where the distance elasticity for the desirable output y, $\varepsilon_{D,y}$, is recovered using the homogeneity condition in the HDF context, $\varepsilon_{D,y} = 1 + \varepsilon_{D,s}$.

Similarly, we derive the marginal product (MP) of an input x_k for the desirable output y using the distance function:

$$MP_{y,x_k} = \frac{\partial y}{\partial x_k} = -\frac{\partial D^H/\partial x_k}{\partial D^H/\partial y} = -\frac{\varepsilon_{D,x_k}}{\varepsilon_{D,y}} \cdot \frac{y}{x_k}. \tag{14}$$

where ε_{D,x_k} is a distance function elasticity of an input x_k. As with the NMRT, the marginal product is computed with normalization by the output-input ratio and evaluated at means. This normalized marginal product (NMP) provides a straightforward interpretation of the relative contribution of input to output, independent of absolute scale. The NMP of input x on output y is expressed as $NMP_{y,x_k} = -\frac{\varepsilon_{D,x_k}}{\varepsilon_{D,y}}$.

We consider one desirable output, average annual employment growth return ($y_c = \exp(\beta_{1,c})$) and one undesirable output, economic instability (s_c), measured by the standard deviation of annual geometric employment growth over the study period for each community c, derived from the regression equation (1).

The input vector includes: (1) population (x_1), representing labor input or human capital for community growth (Himes-Cornell and Hoelting, 2015); (2) wage income per capita (x_2), serving as a proxy for economic development or productivity, reflecting economic capital quality and welfare (Kluge, 2018); (3) an industrial diversification measure (x_3); and (4) a fisheries diversification measure (x_4).[3]

To meet the HDF framework's requirements and enable intuitive interpretation, however, we invert these diversification measures into specialization measures ($1/x_3$ and $1/x_4$). Unlike traditional inputs such as labor and capital, diversification aims for stable, moderate growth with lower risk, aligning with portfolio theory. This unconventional input-output relationship, characterized by lower returns and risks, can complicate interpretation in the HDF context. Inverting diversification into specialization allows us to analyze how specialization influences economic growth and stability while ensuring compliance with the HDF's input properties.

Fisheries-related variables, not directly tied to broader local economy growth—such as (1) the ratio of fishing revenue to wage income (a measure of fishing dependency) and (2) fishing permit share within

[3]We limit the inclusion of variables to a maximum of four input variables that strongly relate to economic growth in fishing communities, based on available community-level data in the HDF. This limitation arises from (1) the exponential increase in the number of parameters with additional input variables in the translog specification with limited degrees of freedom in the data, and (2) potential difficulties in likelihood function convergence as the number of estimated parameters increases.

a shared economic zone (a fishing hotspot (or concentration) index at the borough level)—are included in inefficiency terms.[4] These variables enable heteroskedastic inefficiency, influencing distance function values and promoting efficient economic growth in fishing communities. By reducing unnecessary instability and fostering growth, they capture community-specific characteristics driving heterogeneous inefficiency.

To impose the homogeneity condition, we use the desirable output y_c as the normalizing factor, following Cuesta and Zofío (2005); Cuesta et al. (2009) and Reimer et al. (2017). The resulting normalized distance function is expressed as:

$$
\begin{aligned}
-\ln y_c = \Big(&\alpha_0 + \sum_{k=1}^{4} \alpha_k \ln x_{k,c} + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \alpha_{kl} \ln x_{k,c} \ln x_{l,c} + \delta_1 \ln s_c^* \\
&+ \frac{1}{2}\delta_{11} \ln s_c^* \ln s_c^* + \sum_{k=1}^{4} \eta_{k1} \ln x_{k,c} \ln s_c^*\Big) + v_c + u_c,
\end{aligned}
\tag{15}
$$

where $s_c^* = s_c \cdot y_c$. The hyperbolic distance function (HDF) in Equation (15) allows for efficient output adjustments. Extending this, we additionally use the Enhanced Hyperbolic Distance Function (EHDF) used by Cuesta and Zofío (2005); Cuesta et al. (2009); Dalheimer et al. (2024), which additionally adjusts inputs for greater efficiency. The EHDF, denoted as D^E, normalizes inputs by the desirable output, yielding:

$$
\begin{aligned}
-\ln y_c = \Big(&\alpha_0 + \sum_{k=1}^{4} \alpha_k \ln x_{k,c}^* + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \alpha_{kl} \ln x_{k,c}^* \ln x_{l,c}^* + \delta_1 \ln s_c^* \\
&+ \frac{1}{2}\delta_{11} \ln s_c^* \ln s_c^* + \sum_{k=1}^{4} \eta_{k1} \ln x_{k,c}^* \ln s_c^*\Big) + v_c + u_c,
\end{aligned}
\tag{16}
$$

where $x_{k,c}^* = x_{k,c} \cdot y_c$.

Normalizing inputs and outputs by the homogeneity condition reduces potential simultaneity bias, as outputs appear on both the left and right sides of the equation. This approach allows the use of output ratios as exogenous values since they represent radial expansion while holding input levels constant (Coelli and Perelman, 1996; Coelli, 2000; Cuesta and Orea, 2002). In the EHDF framework, desirable outputs are affected directly by error terms, while inputs (and undesirable outputs) are inversely affected, permitting exogenous treatment of desirable-undesirable output ratio and input-output products normalized by desirable outputs (Cuesta and Zofío, 2005; Dalheimer et al., 2024). For convenient elasticity evaluation at the means

[4] We assume that these variables may directly influence the fishing sector's productivity but not directly impact economic growth and instability, except through their effects on the fishing sector. Therefore, we do not include them in the frontier equation.

and improved convergence in maximum likelihood estimation (MLE), we normalize all variables by their geometric mean, as recommended by Cuesta et al. (2009) and Reimer et al. (2017).

5 Results

We estimate the hyperbolic distance function (HDF) and the enhanced hyperbolic distance function (EHDF) in Equations (15) and (16) using the four inputs defined above. We implement stochastic frontier analysis (SFA) under three specifications that vary the inefficiency determinants: (1) no controls, (2) spatial fishing permit share within the shared economic zone, and (3) the fishing revenue-to-wage income ratio to assess how fishing dependence affects community efficiency.

Table 2 reports estimates for HDF (1)–(3) and EHDF (1^*)–(3^*). Across all specifications, the inputs are statistically significant in first- and/or second-order terms, supporting their inclusion. The signs and significance of the coefficients on average population (α_1), wage income per capita (α_2), industrial specialization (α_3), and fisheries specialization (α_4) are consistent with the HDF's non-increasing property in inputs; in practice, coefficients are significantly negative or not statistically different from zero. Per capita wage income, a proxy for community-specific economic development and productivity, also affects economic growth. Although its first-order effect is generally not significant, higher-order terms are significant in most specifications, suggesting increasing returns to scale in development and productivity.

Economic instability, treated as an undesirable output, also conforms to the non-increasing property: estimates for δ_1 are negative and statistically significant. This pattern is consistent with the high-risk, high-return implication of modern portfolio theory (MPT). We further corroborate this trade-off by testing the output-ratio normalized marginal rate of transformation, $NMRT_{s,y}$, evaluated at sample means (Equation (13)); results appear in Table 3.

Table 2: Estimation results: (enhanced) hyperbolic distance function

	(1)	(2)	(3)	(1*)	(2*)	(3*)
		HDF			**EHDF**	
Population (α_1)	-0.018***	-0.018***	-0.019***	-0.018***	-0.018***	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wage/Capita Inc. (α_2)	0.002	0.001	-0.000	0.001	0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ind. Specialization (α_3)	-0.014*	-0.015*	-0.018**	-0.012	-0.013*	-0.016**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Fish. Specialization (α_4)	-0.007***	-0.007***	-0.007***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Population sq. (α_{11})	0.008***	0.008***	0.009***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wage/Capita Inc. sq. (α_{22})	-0.021	-0.023*	-0.027**	-0.020	-0.022	-0.026*
	(0.046)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Ind. Specialization sq. (α_{33})	-0.001	0.001	-0.005	-0.018	-0.016	-0.021
	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)
Fish. Specialization sq. (α_{44})	0.009**	0.009*	0.010**	0.010**	0.009**	0.010**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Population * Wage/Capita Inc. (α_{12})	-0.007	-0.006	-0.007	-0.005	-0.004	-0.005
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Population * Ind. Special. (α_{13})	0.005	0.005	0.001	0.002	0.002	-0.002
	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
Population * Fish. Special. (α_{14})	0.008***	0.008***	0.008***	0.007***	0.007***	0.008***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Wage/Capita Inc. * Ind. Special. (α_{23})	-0.016	-0.020	-0.027	-0.024	-0.025	-0.030
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Wage/Capita Inc. * Fish. Special. (α_{24})	-0.003	-0.003	-0.004	-0.001	-0.001	-0.002
	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)	(0.053)
Ind. Special. * Fish. Special. (α_{34})	0.015	0.015	0.014	0.016*	0.016*	0.014
	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Econ. Instability (δ_1)	-0.302***	-0.296***	-0.298***	-0.321***	-0.314***	-0.317***
	(0.053)	(0.041)	(0.039)	(0.040)	(0.039)	(0.039)
Econ. Instability sq. (δ_{11})	0.281	0.435	0.369	0.617	0.743	0.664
	(0.912)	(0.929)	(0.942)	(0.860)	(0.875)	(0.886)
Population * Econ. Instability (η_{11})	-0.011	-0.016	-0.016	0.007	0.011	0.007
	(0.042)	(0.041)	(0.041)	(0.040)	(0.040)	(0.040)
Wage/Capita Inc. * Econ. Instability (η_{21})	-0.416***	-0.397***	-0.425***	-0.349***	-0.335***	-0.364***
	(0.115)	(0.116)	(0.114)	(0.114)	(0.113)	(0.112)
Ind. Special. * Econ. Instability (η_{31})	-0.073	-0.091	-0.128	-0.014	-0.022	-0.059
	(0.167)	(0.167)	(0.167)	(0.163)	(0.164)	(0.163)
Fish. Special * Econ. Instability (η_{41})	-0.063	-0.054	-0.061	-0.036	-0.025	-0.028
	(0.050)	(0.051)	(0.051)	(0.050)	(0.050)	(0.050)
Inefficiency						
Broader Permit Share		-0.720	-1.005		-0.717	-1.024*
		(0.734)	(0.645)		(0.703)	(0.618)
Fishing Earnings to Wage Income Ratio			0.051**			0.052**
			(0.025)			(0.023)
Observations	177	177	177	177	177	177

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Our main variables of interest—industrial specialization ($1/x_3$) and fisheries specialization ($1/x_4$) (as inverse diversification)—demonstrate their relevance to economic growth. Notably, fisheries specialization shows its potential role in influencing the economic growth of local economies in fishing communities beyond the fishing sector. To further clarify how these specialization measures affect community economic growth and growth instability, we tested the marginal product using Equation (14), based on the estimated distance function elasticities of specialization measures, economic instability, and economic growth via the implicit function theorem.

Table 3: Test results for the normalized $MRT_{s,y}$

	(1)	(2)	(3)	(1*)	(2*)	(3*)
$NMRT_{s,y}$	2.315***	2.381***	2.350***	2.009***	2.064***	2.018***
	(0.442)	(0.457)	(0.442)	(0.379)	(0.392)	(0.376)

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

For computing the marginal product on employment growth, the distance function elasticity of economic growth ($\epsilon_{D,y}$) was recovered using the homogeneity condition in Equation (10). Table 4 below presents the test results of the computed marginal product of industrial specialization on the employment growth of fishing communities. The overall positive and statistically significant marginal product confirms this relationship between specialization and growth. From the perspective of industrial diversification, this finding suggests that diversification may reduce economic returns. Overall, the statistical significance of the marginal product of industrial specialization on economic growth demonstrates that specialization drives higher economic growth in fishing communities.

Table 4: Test results for the normalized MP_{y,x_3}

	(1)	(2)	(3)	(1*)	(2*)	(3*)
NMP_{y,x_3}	0.020*	0.021*	0.025**	0.020	0.021	0.026*
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

As shown in Table 5, results for fisheries specialization are similar and, in many cases, exhibit higher statistical significance. The computed marginal product of fisheries specialization, MP_{y,x_4}, is strongly significant across all specifications, with a magnitude generally 2–2.5 times lower than that of industrial specialization. Although its effect is smaller than that of industrial specialization, the same interpretation applies: fisheries specialization contributes to higher economic growth in fishing communities beyond the fishing sector. Overall, these findings indicate that specialization—whether in the broader economy or the fishing sector—yields higher economic returns in the local economies of Alaskan fishing communities. Equivalently, diversification (the inverse of specialization) in either fisheries or the local economy reduces economic growth.

Table 5: Test results for the normalized MP_{y,x_4}

	(1)	(2)	(3)	(1*)	(2*)	(3*)
NMP_{y,x_4}	0.010***	0.010***	0.010***	0.009***	0.009***	0.010***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

We also test the marginal products of industrial and fisheries specialization with respect to the undesirable output, economic instability. These marginal products, $MP_{s,x_3} = \frac{\partial s}{\partial x_3}$ and $MP_{s,x_4} = \frac{\partial s}{\partial x_4}$, are obtained via the chain rule as the product of the output trade-off and the effect of specialization on growth:

$$MP_{s,x_k} = \frac{\partial s}{\partial y} \cdot \frac{\partial y}{\partial x_k} = MRT_{s,y} \cdot MP_{y,x_k}, \quad k \in \{3, 4\},$$

because a change in an input first affects the desirable output y (through MP_{y,x_k}), which in turn affects the undesirable output s (through $MRT_{s,y}$).

Table 6: Test results for normalized MP_{s,x_3}

	(1)	(2)	(3)	(1*)	(2*)	(3*)
NMP_{s,x_3}	0.049*	0.051*	0.059**	0.038	0.043*	0.052**
	(0.027)	(0.028)	(0.028)	(0.026)	(0.026)	(0.026)

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The test results for MP_{s,x_3}—the marginal product of industrial specialization on economic instability—generally show a statistically significant positive relationship. Thus, while more industrially specialized fishing communities in Alaska benefit from higher economic growth, they must also contend with greater instability. Interpreting specialization inversely as diversification, communities with more diversified local economies experience greater stability, albeit with a moderate reduction in growth. We also test the marginal product of fisheries specialization; results in Table 7 are consistent with those for industrial specialization.

In sum, both types of specialization (and, inversely, diversification)—in fisheries and in the broader industrial structure—affect local economic performance: specialization raises growth but is associated with higher instability, whereas diversification improves stability at the cost of some growth. The magnitude of these effects is larger for industrial structure than for fisheries, which is expected given the direct relevance of

Table 7: Test results for normalized MP_{s,x_4}

	(1)	(2)	(3)	(1*)	(2*)	(3*)
NMP_{s,x_4}	0.024***	0.023***	0.024***	0.019***	0.018***	0.019**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

industrial composition to the local economy, while fisheries diversification primarily influences the fishing sector with second-order effects on the broader economy.

The interaction-term coefficients between inputs, α_{kl}, capture complementary and substitution relationships in the production process (Morrison-Paul et al., 2000; Cuesta et al., 2009). Following Morrison-Paul et al. (2000)[5], a positive coefficient $\alpha_{kl} > 0$ indicates substitution, where the marginal product of input k decreases as input l increases (by symmetry, $\alpha_{kl} = \alpha_{lk}$). Conversely, a negative coefficient $\alpha_{kl} < 0$ indicates complementarity, where the marginal product of input k increases with input l.

A key result is the significance of the interaction between fisheries and industrial specialization. Estimates for α_{34} indicate substitution between these inputs: statistically significant in the EHDF and marginally significant in the HDF ($p < 0.13$ for HDF (1)–(3)). This suggests that fisheries and industrial specialization can substitute for each other, with implications for economic development in Alaskan fishing communities.

If physical or economic constraints limit specialization in the local economy, communities may instead specialize in fisheries to achieve growth. Conversely, if fisheries specialization is constrained by ecological or market factors, communities may specialize within a particular industrial sector. Thus, when specialization in one domain is constrained by geography or resource availability, communities may compensate by specializing in the other.

From the diversification perspective (the inverse of specialization), this implies complementarity between specialization and diversification across fisheries and the local fishing economy. Specializing in one domain while diversifying the other can support sustainable growth with greater stability. Balancing specialization and diversification across industrial sectors and fisheries creates a complementary dynamic that fosters stability without sacrificing growth.[6]

[5]Unlike most of the distance-function literature, which uses a negative sign on the left-hand side for normalization, Morrison-Paul et al. (2000) use a positive sign to simplify interpretation of production relationships. By flipping the sign of our estimated coefficients, we provide an interpretation consistent with Morrison-Paul et al. (2000). Similarly, Cuesta et al. (2009) use a negative sign but provide the same interpretation.

[6]As a robustness check, we re-estimate this complementary relationship using a direct diversification measure and assess which direction of complementarity is clearer (i.e., industrial diversification & fisheries specialization vs. industrial specialization & fisheries diversification).

In the SFA inefficiency equations that allow for heteroskedastic inefficiency with respect to fisheries-related community factors, the fisheries-permit share (a fisheries concentration index) shows a negative sign consistently, which aligns with challenges faced by small fishing communities with limited access to fishing-support services (Lavoie and Himes-Cornell, 2019). Survey and network evidence indicate that remote Alaskan fishing communities rely heavily on larger hub communities (e.g., Anchorage, Homer, Wrangell, Fairbanks, Ketchikan, Sitka, Kodiak) for infrastructure and services; this reliance is associated with higher fishing costs and reduced adaptive capacity to climate-related shocks.

Lastly, the fishing-dependency variable is positively associated with inefficiency, indicating that higher dependence on fishing coincides with greater distance from the production frontier. This association is consistent with lower economic growth and greater instability, underscoring that heavy reliance on natural resources may hinder efficient growth in fishing communities.

5.1 Robustness check 1: Testing endogeneity of input variables

Our objective is to develop a comprehensive understanding of how industrial and fisheries diversification shape growth and stability in local fishing economies, and how they interact with other growth factors in Alaska's fishing communities, rather than to identify variable-specific causal effects. Nevertheless, endogeneity remains a concern that could complicate interpretation.

We have argued that our HDF estimates are relatively robust to endogeneity, particularly simultaneity. Even so, unobserved community characteristics may influence input variables and economic instability, and the limited literature on community growth determinants, together with scarce community-level data, leaves residual uncertainty.

Empirical studies often mitigate endogeneity by incorporating additional data (e.g., input prices) or by using instrumental variables (IV) within SFA (Dalheimer et al., 2024; Sauer and Latacz-Lohmann, 2015; Atkinson et al., 2003). Applying IV methods in SFA is challenging: valid community-level instruments are difficult to find; even with valid instruments, our setting faces (1) a modest cross-sectional sample (few communities), (2) substantial consumption of degrees of freedom due to numerous parameters, and (3) potential weak-instrument problems, particularly in the translog HDF. As Amsler et al. (2016) note, addressing endogeneity in a translog specification with multiple endogenous variables requires instruments for nonlinearly transformed terms (squares and interactions), which may be weak; in such cases, two-stage estimators (e.g., 2SLS) can be statistically inefficient.

A potential alternative is the True Fixed-Effects (TFE) model in SFA (Greene, 2005a,b), which can address omitted time-invariant community factors. However, TFE estimation suffers from the incidental-parameter problem in panels with many communities (N large) and a fixed, finite time dimension (T small).

As a robustness check, we therefore test for potential endogeneity using the Bayesian Mundlak–Chamberlain device (MCD), which models unobserved heterogeneity and helps validate our results. Following Dalheimer et al. (2024), who apply an HDF framework with comparable inputs, desirable outputs, and undesirable outputs, we implement the Bayesian MCD. The device originates with Mundlak (1978) and Chamberlain (1982) and is extended to a Bayesian framework by Griffiths and Hajargasht (2016); it is well suited to SFA contexts.

The Mundlak–Chamberlain device (MCD) addresses endogeneity in panel models by modeling the correlation between unit effects and observed regressors. Like fixed effects, it mitigates bias from omitted variables correlated with both the dependent variable and the inputs. Relative to fixed effects, MCD estimation (1) preserves between variation, improving efficiency; (2) flexibly accommodates nonlinear models while capturing unobserved heterogeneity; and (3) avoids the incidental-parameter problem because it does not estimate unit-specific intercepts (Wooldridge, 2010).

Building on this idea, Griffiths and Hajargasht (2016) propose a Bayesian test for input endogeneity in SFA, subsequently applied by Dalheimer et al. (2024). The model is:

$$\ln y_{it} = \ln f(X_{it}, s_{it}; \beta) - u_i + v_{it}, \tag{17}$$

$$H(u_i) = \bar{x}_i{}'\delta + \zeta_{it}, \tag{18}$$

where $H(u_i) = \ln(u_i)$ and $f(\cdot)$ is a Cobb–Douglas distance function.[7] The inefficiency specification $H(\cdot)$ includes time-averaged values $\bar{x}_i$ of industrial (x_3) and fisheries specialization (x_4) to test for endogeneity. Unlike frequentist confidence intervals, Bayesian credible intervals admit a direct probabilistic interpretation of parameter uncertainty given the data and priors.

Statistically significant posterior means in the inefficiency equation within a given credible interval (e.g., 95%) indicate potential endogeneity (Griffiths and Hajargasht, 2016; Dalheimer et al., 2024). Conversely, insignificance—evidenced by a large posterior standard deviation relative to the mean—implies weak evi-

[7]Following Griffiths and Hajargasht (2016) and Dalheimer et al. (2024), we adopt Cobb–Douglas for computational efficiency in sampling and convergence.

dence of endogeneity. In Bayesian terms, the credible interval for the correlation parameters δ quantifies this uncertainty; wide intervals centered near zero suggest weak correlation.

We adopt the priors in Griffiths and Hajargasht (2016) for the frontier parameters β and the inefficiency parameters δ. To form the panel, we split the study period into two blocks, 2000–2008 and 2009–2016, yielding a structure that balances long-run trends and data availability. After excluding communities with insufficient time observations, the sample comprises $N = 165$ communities observed over $T = 2$ periods ($NT = 330$). Table 8 reports the Bayesian MCD estimates.

Table 8: Results from Bayesian Mundlak–Chamberlain device estimation.

$\ln y_1$	**Posterior Mean**	**Posterior SD**
Frontier		
Const.	0.233	0.208
$\ln x_1$ (Population)	2.770**	0.642
$\ln x_2$ (Wage Income per Capita)	0.413	0.457
$\ln x_3$ (Ind. Specialization)	1.707**	0.647
$\ln x_4$ (Fish. Specialization)	-0.759	0.430
$\ln s_1$ (Instability)	15.790**	6.829
Inefficiency		
Const.	-1.821**	0.918
$\overline{\ln x_3}$	0.008	1.409
$\overline{\ln x_4}$	0.006	1.422
Sample Observations	330	

** Significant at the 95% credible interval level.

We find no strong evidence of endogeneity for industrial or fisheries specialization, suggesting that endogeneity is not a major concern in our HDF model. The Bayesian estimates closely align with the HDF results: population (x_1) and industrial specialization (x_3) have positive effects on economic growth, while wage per capita (x_2) is insignificant. Fisheries specialization (x_4) is not significant, which may reflect the short panel length or specification differences (e.g., inclusion of quadratic terms). Instability shows a significant positive association with employment growth, reinforcing the link between higher growth and greater instability. Overall, the Bayesian MCD results support our main findings.

5.2 Robustness check 2: Estimation with direct diversification measures

In our main estimation, we invert industrial and fisheries diversification to interpret specialization and to maintain the non-increasing property of inputs, consistent with conventional input–output relationships in the HDF framework. To confirm robustness, we also estimate the model using direct diversification measures. This provides direct evidence of the complementary relationship between fisheries diversification (or specialization) and economic specialization (or diversification), rather than relying solely on indirect inference from specialization in the main analysis. Switching from fisheries specialization to its direct diversification counterpart yields coefficients with the same significance but opposite signs.

Complete results appear in Table C1 in Appendix C, which reports HDF estimates using the direct diversification measure (fisheries diversification, the inverse of specialization). The results align with our primary findings: the signs and significance of fisheries diversification and its interaction terms are consistent, with coefficients of similar magnitude but opposite signs. In addition, the interaction between fisheries diversification and economic specialization reaffirms the complementary relationship between diversification and specialization.

5.3 Robustness check 3: Estimation with alternative diversification measures using the Herfindahl–Hirschman index

We examine the sensitivity of our results to alternative diversification measures. In place of our default measure (based on the Shannon diversity index), we construct an alternative index using the inverse Herfindahl–Hirschman Index (HHI), also known as the Simpson diversity index, following Kluge (2018). Like the Shannon index, this measure is lower-bounded by 1. We define the inverse-HHI diversification index, Div_c^{HHI}, using sector shares P_{ict} (as in Equation (2)) as:

$$Div_c^{HHI} = \frac{1}{T} \sum_{t=1}^{T} \left(\frac{1}{\sum_{i=1}^{N} P_{ict}^2} \right). \tag{19}$$

Table D1 in Appendix D reports estimates using this alternative index (converted to a specialization measure for estimation). Results are qualitatively consistent with the baseline that uses the Shannon index, differing only slightly in magnitude because the two measures are on different scales.[8]

[8] A simple correlation analysis shows strong agreement between the two indices: the correlation coefficient is 0.97 for both industrial and fisheries diversification. These findings confirm that our main results are robust to the choice of diversification measure.

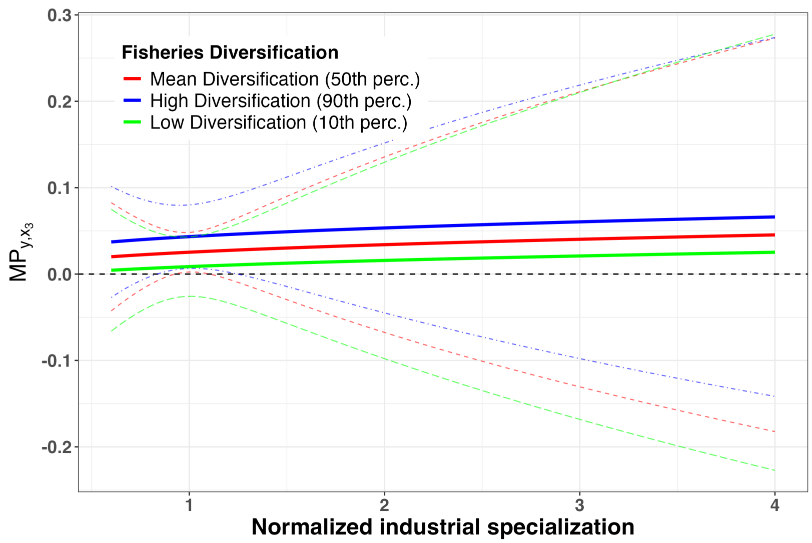
6 Discussion

The growth and stability of Alaska's local fishing economies are critical for sustaining fishing communities and fishers' livelihoods as climate-induced changes reshape ocean and coastal systems. Prior research on fisheries diversification has largely focused on stabilizing revenue within the fishing sector, often extrapolating broader community effects without direct empirical evidence. We address this gap by providing empirical evidence that fisheries diversification—alongside industrial diversification within the local economy—shapes the growth and stability of local fishing economies. In particular, both fisheries and industrial diversification are associated with greater stability in the local economies of fishing communities.

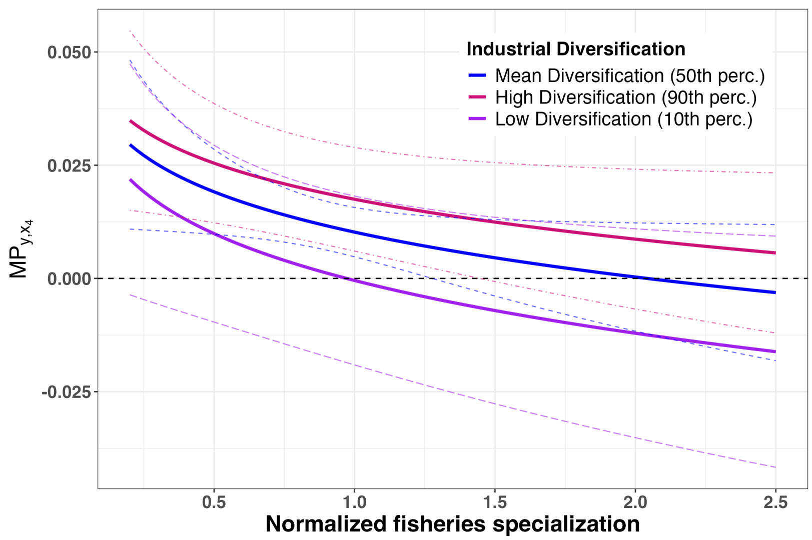
Our research provides the first empirical evidence that industrial and fisheries diversification are interlinked with each other and with broader community growth factors in shaping local economic growth. We find potential synergistic effects, where fisheries specialization and industrial diversification reinforce one another. Figure 4 shows the marginal product of each specialization across varying diversification levels in the complementary sector.

Figure 4a shows that the marginal product of industrial specialization increases monotonically with little evidence of diminishing returns. Greater fisheries diversification shifts this curve upward, indicating synergy; however, statistical precision is weaker for the industrial specialization estimates, as reflected in wide 95% confidence intervals. For fisheries specialization (Figure 4b), the marginal product exhibits diminishing returns: at very high levels of specialization, additional specialization can reduce local economic growth. As with industrial specialization, greater industrial diversification raises the marginal product curve and moderates the rate of diminishing returns. Moreover, the synergistic direction is statistically clearer for fisheries specialization than the complementary effect associated with industrial specialization. Overall, our results—supported by both estimations and visualizations—demonstrate that economic growth and stability in local fishing economies, driven by industrial and fisheries diversification, exhibit heterogeneous responses significantly influenced by the interaction with diversification levels in the complementary counterpart, whether in fisheries or the industrial structure of communities.

Previous studies have focused on the stabilizing effects of diversification while overlooking its trade-off with long-term growth. This narrow focus risks neglecting the vital role of economic growth in sustaining local fishing economies. Our findings show that, on average, Alaskan fishing communities have experienced a zero-growth steady state in employment, suggesting that achieving stability at the expense of growth



(a) Industrial specialization on growth



(b) Fisheries specialization on growth

Figure 4: Marginal products of industrial and fisheries specialization with complementary effects. Dashed lines denote 95% confidence intervals computed via the delta method (Appendix E). Estimates are based on specification (3) in Table 2 and are evaluated at the sample means of the other covariates. We use the HDF specification for interpretability because the EHDF case normalizes input x.

may undermine sustainability. Therefore, a balanced approach that fosters both economic stability and growth—whether through fisheries diversification or a specialized industrial structure—is essential for long-term viability.

Sethi et al. (2014) noted that geographical factors may constrain fisheries diversification, thus limiting its potential to drive economic stability or growth in certain contexts. In line with this, our findings suggest that economic stability can still be achieved through industrial structural improvements, provided that geographic constraints do not also restrict industrial reform. Communities can pursue industrial specialization for direct growth or diversification to enhance growth—particularly in support of specialized fisheries through the complementary effects shown in Figure 4. This dual-track strategy enables fishing communities to achieve balanced economic growth and stability by adapting fisheries and industrial structures to their specific community contexts, minimizing trade-offs between economic growth and stability.

Figure 4 further reveals that the complementary effects between fisheries specialization and industrial diversification are more evident than those between industrial specialization and fisheries diversification. While specializing in high-yield fisheries can drive revenue growth and generate spillover effects, it also heightens vulnerability to market and ecological shocks. A diversified industrial base—including processing, logistics, tourism, and trade—provides essential complementary services and alternative income sources during fisheries downturns. Consequently, fisheries-specialized communities may need to enhance resilience against a rapidly changing fishing environment by pursuing industrial diversification.

Overall, our research offers several key policy insights. First, fisheries policies alone are insufficient; they must be integrated with broader industrial development strategies to sustain local fishing economies. Second, place-based interventions that promote cross-sector investments and industrial diversification are essential for balancing the trade-off between economic growth and stability. Finally, tailored workforce development and community-specific strategies are crucial, as the optimal transformation of industrial structure depends on local conditions. Collectively, these insights highlight the need for a comprehensive, locally attuned policy framework to foster resilient and sustainable economic growth in Alaska's fishing communities.

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Appendix

A Estimation procedure details in stochastic frontier analysis

Our SFA employs a simultaneous estimation of the efficient frontier and inefficiency equations using Maximum Likelihood Estimation (MLE), avoiding the biases of the traditional two-step approach. To ensure reliable results, we address three critical factors: (i) the distributional assumption for the inefficiency term, (ii) initial parameter selection, and (iii) the optimization algorithm. These steps are essential to prevent convergence issues, avoid local maxima, and produce robust parameter estimates.

To determine initial values for maximizing the likelihood function, we followed the approach outlined by Kumbhakar et al. (2015). Specifically, we began by performing Ordinary Least Squares (OLS) estimations on both the frontier and inefficiency equations. The resulting coefficients were then used as initial values for the subsequent SFA process. This method provides a robust foundation for the optimization process and improves the reliability and precision of our estimations, particularly in cases where the default initial values generated by STATA may not perform adequately.

After evaluating both half-normal and truncated-normal distributions and finding non-significant results for the mean locus of the truncated-normal distribution, we opted for the half-normal distribution as proposed by Aigner et al. (1977), which is generally employed in the HDF literature. This choice was made for its simplicity and effectiveness in estimating the likelihood function, attributed to its single-parameter characteristic, unlike the two-parameter (mean locus and standard deviation) structure of the truncated-normal distribution.[9]

The selection of an optimization algorithm for the likelihood function significantly influences the stability and convergence of the likelihood function. Within our estimation environment, specifically STATA, we utilized four different optimization algorithms.[10] After experimenting with these algorithms, we identified those that exhibited stable convergence of the likelihood function, along with the highest likelihood value upon stable convergence. This approach ensures that our choice of optimization algorithm not only promotes efficient convergence but also optimizes the accuracy and reliability of our estimation results.

[9] Exponential and gamma distributions were also considered but the half-normal and truncated-normal distributions showed superior convergence in our preliminary analysis, leading us to focus on these distributions.

[10] Newton-Raphson, Broyden–Fletcher–Goldfarb–Shanno (BFGS), Davidon–Fletcher–Powell (DFP), and Berndt–Hall–Hall–Hausman (BHHH).

B Measuring economic growth rate and economic instability

In our study, we utilized the geometric growth rate of employment as our measure for average growth. This metric is often employed to present a more accurate long-term performance of a portfolio. It is based on the principle that performance in one period affects subsequent periods. Conversely, the arithmetic average may not accurately measure long-term growth when economic volatility is prevalent.

We adopt the methodologies utilized by Lande (1994), Chandra (2002), and Hafner (2019). To elucidate this approach, we begin with a continuous-time exponential model for employment growth rate, which is expressed as:

$$Emp_t = Emp_0 \cdot e^{\beta_1 \cdot t}$$

Here, Emp_0 represents the initial employment at time $t = 0$, and β_1 is the instantaneous employment growth rate. By logarithmically transforming both sides of the equation, we obtain:

$$\log(Emp_t) = \beta_0 + \beta_1 \cdot t$$

where β_0 = $\log(Emp_0)$, treated as a constant. This log-transformed equation, after including an error term ϵ_t, is estimated using Ordinary Least Squares (OLS) as follows:

$$\log(Emp_t) = \beta_0 + \beta_1 \cdot t + \epsilon_t$$

With the estimated coefficient of the time trend, $\hat{\beta}_1$, interpreted as the average instantaneous growth rate of employment, we difference the estimated equation from $t - 1$ to t:

$$\log(Emp_t) - \log(Emp_{t-1}) = \hat{\beta}_1$$

By exponentiating the above equation and recognizing that the discrete-time version of exponential growth corresponds to the geometric growth rate, we establish the following relationship:

$$(1 + \mu) = \exp(\hat{\beta}_1)$$

where μ represents the average annual geometric growth rate of employment for a community. Since the

HDF employs a log-transformation to ensure all values remain positive, we use the average annual geometric growth *return*, $y_c = \exp(\beta_1, c)$, where the subscript c denotes each community.

Subsequently, instability is quantified as the standard deviation of residuals from an OLS estimation based on the previous log-time trend equation. The fitted regression line on the time trend captures the long-term (geometric) return; thus, larger deviations from this fitted line, whether positive or negative, are interpreted as economic instability associated with year-to-year economic growth. The sum of squared residuals is computed as follows:

$$\sum_{t=1}^{T} \left(\ln Emp_t - \ln E\hat{m}p_t\right)^2 = \sum_{t=1}^{T} \left(\ln \frac{Emp_t}{E\hat{m}p_t}\right)^2$$

Along with the geometric mean, the formula for geometric standard deviation (GSD), σ_g, is expressed as an exponentiated arithmetic mean of the logged differences between some values A_n and their geometric mean μ_g over a number of observations N as follows:

$$\text{GSD} = \sigma_g = \exp\left(\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\ln \frac{A_n}{\mu_g}\right)^2}\right).$$

Following this formula, the equivalent growth instability of fishing community c, as the geometric standard deviation of the long-term growth trend, can be derived using the fitted mean regression line on time trend ($\ln(E\hat{m}p_t) = \hat{\beta}_0 + \hat{\beta}_1 \cdot t$), as follows. The economic instability of community c, represented as the geometric standard deviation of economic growth, is given by:

$$\sigma_c = s_c = \exp\left(\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\ln \frac{Emp_t}{E\hat{m}p_t}\right)^2}\right).$$

C Robustness check using direct diversification measure

Table C1: Estimation results for robustness check: using fisheries diversification

	(1)	(2)	(3)	(1*)	(2*)	(3*)
	HDF			EHDF		
Population (α_1)	-0.017***	-0.018***	-0.019***	-0.018***	-0.018***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wage/Capita Inc. (α_2)	0.002	0.001	-0.000	0.001	0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ind. Specialization (α_3)	-0.014*	-0.015*	-0.018**	-0.012	-0.013*	-0.016**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Fish. Diversification (α_4)	0.007***	0.007***	0.007***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Population sq. (α_{11})	0.008***	0.008***	0.009***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wage/Capita Inc. sq. (α_{22})	-0.021	-0.023*	-0.027**	-0.020	-0.022	-0.026*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Ind. Specialization sq. (α_{33})	-0.002	0.001	-0.005	-0.018	-0.016	-0.021
	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)
Fish. Diversification sq. (α_{44})	0.010**	0.009*	0.010**	0.010**	0.009*	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Population * Wage/Capita Inc. (α_{12})	-0.006	-0.006	-0.007	-0.005	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Population * Ind. Special. (α_{13})	0.005	0.005	0.001	0.002	0.002	-0.002
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Population * Fish. Div. (α_{14})	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wage/Capita Inc. * Ind. Special. (α_{23})	-0.017	-0.018	-0.023	-0.023	-0.025	-0.030
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Wage/Capita Inc. * Fish. Div. (α_{24})	0.003	0.003	0.004	0.001	0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Econ Special. * Fish. Div. (α_{34})	-0.015	-0.015	-0.013	-0.016*	-0.016*	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Econ. Instability (δ_1)	-0.302***	-0.296***	-0.298***	-0.321***	-0.314***	-0.317***
	(0.040)	(0.040)	(0.039)	(0.040)	(0.039)	(0.039)
Econ. Instability sq (δ_{11})	0.281	0.420	0.370	0.617	0.743	0.664
	(0.912)	(0.929)	(0.942)	(0.860)	(0.875)	(0.886)
Population * Econ. Instability (η_{11})	-0.017	-0.014	-0.016	-0.007	-0.010	-0.007
	(0.041)	(0.041)	(0.041)	(0.040)	(0.041)	(0.040)
Wage/Capita Inc. * Econ. Instability (η_{21})	-0.416***	-0.402***	-0.425***	-0.349***	-0.336***	-0.364***
	(0.116)	(0.115)	(0.114)	(0.114)	(0.113)	(0.111)
Ind. Special. * Econ. Instability (η_{31})	-0.073	-0.083	-0.116	-0.014	-0.022	-0.059
	(0.167)	(0.167)	(0.167)	(0.162)	(0.163)	(0.163)
Fish. Diversification * Econ. Instability (η_{41})	0.064	0.053	0.055	0.038	0.025	0.028
	(0.050)	(0.051)	(0.051)	(0.049)	(0.050)	(0.050)
Inefficiency						
Broader Permit Share		-0.720	-1.004		-0.717	-1.024*
		(0.734)	(0.644)		(0.703)	(0.618)
Fishing Earnings to Wage Income Ratio			0.051**			0.052**
			(0.025)			(0.023)
Observations	177	177	177	177	177	177

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D Robustness check using alternative diversification measure with inverse HHI index

Table D1: Estimation results for robustness check: using an alternative diversification measure (inverse HHI)

	(1)	(2)	(3)	(1*)	(2*)	(3*)
		HDF			**EHDF**	
Population (α_1)	-0.017***	-0.018***	-0.018***	-0.018***	-0.018***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wage/Capita Inc. (α_2)	0.002	0.001	0.000	0.001	0.000	-0.001
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Ind. Specialization (α_3)	-0.014*	-0.015**	-0.017**	-0.012	-0.013*	-0.016**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Fish. Diversification (α_4)	-0.009***	-0.008***	-0.009***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Population sq. (α_{11})	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Wage/Capita Inc. sq. (α_{22})	-0.020	-0.023*	-0.026*	-0.020	-0.022	-0.026*
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Ind. Specialization sq. (α_{33})	0.015	0.018	0.017	-0.018	-0.016	-0.021
	(0.047)	(0.047)	(0.047)	(0.044)	(0.044)	(0.044)
Fish. Diversification sq. (α_{44})	0.012**	0.011*	0.011*	0.010**	0.009*	0.010**
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Population * Wage/Capita Inc. (α_{12})	-0.005	-0.005	-0.005	-0.005	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Population * Ind. Special. (α_{13})	0.007	0.008	0.005	0.002	0.002	-0.002
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Population * Fish. Div. (α_{14})	0.008***	0.008***	0.009***	0.008***	0.007***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Wage/Capita Inc. * Ind. Special. (α_{23})	-0.009	-0.011	-0.013	-0.023	-0.025	-0.030
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)
Wage/Capita Inc. * Fish. Div. (α_{24})	-0.004	-0.004	-0.005	-0.001	-0.001	0.002
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Econ Special. * Fish. Div. (α_{34})	0.018	0.018	0.016	-0.016*	-0.016*	-0.014
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Econ. Instability (δ_1)	-0.307***	-0.301***	-0.303***	-0.321***	-0.314***	-0.317***
	(0.040)	(0.040)	(0.039)	(0.040)	(0.039)	(0.039)
Econ. Instability sq. (δ_{11})	0.138	0.298	0.231	0.617	0.743	0.664
	(0.897)	(0.918)	(0.935)	(0.860)	(0.875)	(0.886)
Population * Econ. Instability (η_{11})	-0.017	-0.015	-0.016	-0.007	-0.010	-0.007
	(0.038)	(0.038)	(0.038)	(0.040)	(0.041)	(0.040)
Wage/Capita Inc. * Econ. Instability (η_{21})	-0.454***	-0.440***	-0.459***	-0.349***	-0.336***	-0.364***
	(0.112)	(0.111)	(0.111)	(0.114)	(0.113)	(0.111)
Ind. Special. * Econ. Instability (η_{31})	-0.084	-0.098	-0.121	-0.014	-0.022	-0.059
	(0.166)	(0.167)	(0.168)	(0.162)	(0.163)	(0.163)
Fish. Diversification * Econ. Instability (η_{41})	-0.078	-0.065	-0.066	-0.036	-0.025	-0.028
	(0.055)	(0.056)	(0.057)	(0.049)	(0.050)	(0.050)
Inefficiency						
Broader Permit Share		-0.728	-0.950		-0.717	-1.024*
		(0.695)	(0.633)		(0.703)	(0.618)
Fishing Earnings to Wage Income Ratio			0.044*			0.052**
			(0.026)			(0.023)
Observations	177	177	177	177	177	177

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

E Constructing 95% confidence intervals for MP_{y,x_3,x_4}

We outline the detailed procedure for constructing a confidence interval for the marginal product (MP) of input to output, calculated as the ratio of two distance elasticities. These elasticities are derived from differentiating the hyperbolic distance function (HDF). Because the elasticities, except for the variable of interest, are evaluated at their mean values, the remaining logged variables become zero after normalization by geometric means. This approach allows us to examine how the MP changes with respect to a single variable of interest—industrial or fisheries specialization—while holding all other factors constant (*ceteris paribus*). For illustrative purposes, we focus on the procedure for industrial specialization. The distance elasticities for industrial specialization and employment growth are presented below.

$$\epsilon_{D,x3} = \alpha_3 + \alpha_{33} \log(x3)$$

$$\epsilon_{D,y} = 1 + \delta_1 + \eta_{31} \log(x3)$$

Our goal is to compute the variance of $MP_{y,x3}$, which is the ratio of these elasticities:

$$MP = R(\epsilon_{D,x3}, \epsilon_{D,y}) = -\frac{\epsilon_{D,x3}}{\epsilon_{D,y}}$$

To find the variance of R, we use the Delta Method, which provides an approximation for the variance of a function of random variables. The Delta Method states that for a function $g(\boldsymbol{\theta})$ of random variables $\boldsymbol{\theta}$, the variance of $g(\boldsymbol{\theta})$ can be approximated as:

$$\text{Var}[g(\boldsymbol{\theta})] \approx \nabla g(\boldsymbol{\theta})^{\top} \boldsymbol{\Sigma} \nabla g(\boldsymbol{\theta})$$

where $\nabla g(\boldsymbol{\theta})$ is the gradient vector of partial derivatives of g with respect to $\boldsymbol{\theta}$, and $\boldsymbol{\Sigma}$ is the covariance matrix of $\boldsymbol{\theta}$.

We begin by computing the partial derivatives of R with respect to $\epsilon_{D,x3}$ and $\epsilon_{D,y}$:

$$\frac{\partial R}{\partial \epsilon_{D,x3}} = -\frac{1}{\epsilon_{D,y}}$$

$$\frac{\partial R}{\partial \epsilon_{D,y}} = -\left(-\frac{\epsilon_{D,x3}}{\epsilon_{D,y}^2}\right) = \frac{\epsilon_{D,x3}}{\epsilon_{D,y}^2}$$

Applying the Delta Method, the variance of R is approximated as:

$$\mathrm{Var}(R) \approx \left(\frac{\partial R}{\partial \epsilon_{D,x3}}\right)^2 \mathrm{Var}(\epsilon_{D,x3}) + \left(\frac{\partial R}{\partial \epsilon_{D,y}}\right)^2 \mathrm{Var}(\epsilon_{D,y}) + 2\left(\frac{\partial R}{\partial \epsilon_{D,x3}}\right)\left(\frac{\partial R}{\partial \epsilon_{D,y}}\right) \mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y})$$

Substituting the expressions for the partial derivatives:

$$\mathrm{Var}(R) \approx \left(-\frac{1}{\epsilon_{D,y}}\right)^2 \mathrm{Var}(\epsilon_{D,x3}) + \left(\frac{\epsilon_{D,x3}}{\epsilon_{D,y}^2}\right)^2 \mathrm{Var}(\epsilon_{D,y}) + 2\left(-\frac{1}{\epsilon_{D,y}}\right)\left(\frac{\epsilon_{D,x3}}{\epsilon_{D,y}^2}\right) \mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y})$$

Simplifying the expression:

$$\mathrm{Var}(R) \approx \frac{\mathrm{Var}(\epsilon_{D,x3})}{\epsilon_{D,y}^2} + \frac{\epsilon_{D,x3}^2 \mathrm{Var}(\epsilon_{D,y})}{\epsilon_{D,y}^4} - \frac{2\epsilon_{D,x3} \mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y})}{\epsilon_{D,y}^3}$$

Next, we compute the variances of $\epsilon_{D,x3}$ and $\epsilon_{D,y}$. Since $\epsilon_{D,x3}$ is a linear combination of α_3 and α_{33}, its variance is:

$$\mathrm{Var}(\epsilon_{D,x3}) = \mathrm{Var}(\alpha_3) + [\log(x3)]^2 \mathrm{Var}(\alpha_{33}) + 2\log(x3) \mathrm{Cov}(\alpha_3, \alpha_{33})$$

However, as the covariance $\mathrm{Cov}(\alpha_3, \alpha_{33})$ is negligible in our estimations, we simplify:

$$\mathrm{Var}(\epsilon_{D,x3}) \approx \mathrm{Var}(\alpha_3) + [\log(x3)]^2 \mathrm{Var}(\alpha_{33})$$

Similarly, the variance of $\epsilon_{D,y}$ is:

$$\mathrm{Var}(\epsilon_{D,y}) = \mathrm{Var}(\delta_1) + [\log(x3)]^2 \mathrm{Var}(\eta_{31}) + 2\log(x3) \mathrm{Cov}(\delta_1, \eta_{31})$$

Assuming $\mathrm{Cov}(\delta_1, \eta_{31})$ is negligible, we have:

$$\mathrm{Var}(\epsilon_{D,y}) \approx \mathrm{Var}(\delta_1) + [\log(x3)]^2 \mathrm{Var}(\eta_{31})$$

The covariance between $\epsilon_{D,x3}$ and $\epsilon_{D,y}$ is given by:

$$\mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y}) = \mathrm{Cov}(\alpha_3 + \alpha_{33} \log(x3), \delta_1 + \eta_{31} \log(x3))$$

Expanding this covariance:

$$\mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y}) = \mathrm{Cov}(\alpha_3, \delta_1) + \log(x3)[\mathrm{Cov}(\alpha_3, \eta_{31}) + \mathrm{Cov}(\alpha_{33}, \delta_1)] + [\log(x3)]^2 \mathrm{Cov}(\alpha_{33}, \eta_{31})$$

In our estimation, the covariance $\mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y})$ consists of covariances between various parameters, $\alpha_3, \delta_1, \eta_{31}, \alpha_{33}$, which include a mix of negative and positive values, thus, the sum of the terms are close to zero. These terms are multiplied by $\log(x3)$ and $[\log(x3)]^2$, further reducing their already small magnitude. For simplicity and based on this justification, we assume the covariance between these two elasticities is negligible, effectively zero:

$$\mathrm{Cov}(\epsilon_{D,x3}, \epsilon_{D,y}) \approx 0$$

With this assumption, the simplified variance of R, derived using the delta method, becomes:

$$\mathrm{Var}(MP_{y,x_3}) \approx \frac{\mathrm{Var}(\epsilon_{D,x3})}{\epsilon_{D,y}^2} + \frac{\epsilon_{D,x3}^2 \mathrm{Var}(\epsilon_{D,y})}{\epsilon_{D,y}^4}$$

Once the variance is computed, the 95% confidence interval for the marginal product of x_3 is constructed using its root-squared value. For the marginal product related to fisheries specialization, an identical procedure is followed.