# Do Policies with Limited Enforcement Reduce Harm? Evidence from Transshipment Bans

Hamsa Bastani
Wharton School, Operations Information and Decisions, hamsab@wharton.upenn.edu

Joann F. de Zegher
MIT Sloan School of Management, Operations Management, jfz@mit.edu

To mitigate environmental and social harm in supply chains, buyers often provide incentives or impose sanctions to discourage harmful behavior by suppliers. However, such policies are often implemented with limited monitoring and enforcement; theory suggests that such conditions may cause strategic behavior by suppliers, leading to unintended consequences. We study empirically if a policy with limited enforcement (1) can reduce harm, (2) leads to evasion and strategic behavior, and (3) increases raw material costs. We study these questions in the context of a ban on seafood transshipments. Seafood transshipments have been associated with illegal fishing and widespread forced labor in seafood supply chains, leading to pressure on seafood buyers to ban transshipments in their supply chain. Buyers have argued against such a ban, indicating that it would simply lead to evasion (because transshipments are difficult to monitor), while increasing costs (because transshipments allow for more efficient logistics). Directly studying the effect of a supply chain ban by buyers is difficult; instead, we study the effect of geographic bans implemented by international management organizations, and show that the resulting findings provide a conservative estimate of the effect of a supply chain ban. Using remote sensing data and exploiting variation over time and across regions, we find that a geographic ban reduces transshipments by 57% despite significant enforcement challenges. A difference-in-difference analysis of landing prices suggests that this reduction comes at a cost of 3.2% higher prices. In contrast to theoretical predictions, the ban does *not* appear to cause significant strategic evasion.

*Key words*: transshipments, remote sensing, strategic behavior, IUU fishing, forced labor

## 1. Introduction

Seafood is the world's most widely traded food commodity (Bellman et al. 2016), and the seafood sector may be the world's largest employer, employing 260-800 million workers (Teh and Sumaila 2013, Nakamura et al. 2018). Seen as a source of cheap and healthy protein, seafood makes up 20% of the global intake of animal protein (The Guardian 2017). Notably, the majority of the sector's exports (65-70%) are produced in developing countries (UN FAO 2016).

Unfortunately, this large industry faces significant concerns about environmental and social harm in its supply chains. About 20% of global fish catch is caught illegally (Pramod et al. 2017, 2014, Agnew et al. 2009), and there are widespread incidences of forced labor and human trafficking in fishing hub countries like Indonesia, Thailand, Vietnam, the Philippines, and Peru (Nakamura et al. 2018, US DOL 2016, McDowell et al. 2015, Teh and Sumaila 2013). A recent report by the

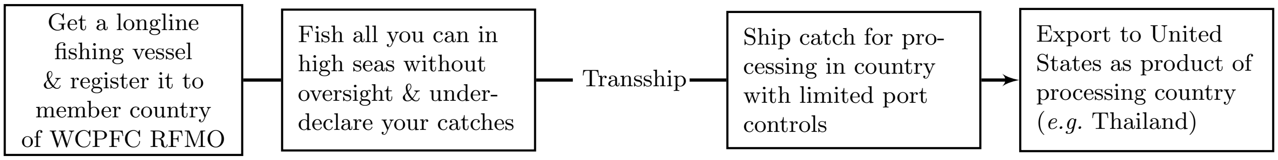


**Figure 1** **Infographic based on Zimmer (2017) on how transshipments enable fish laundering in the Pacific Ocean, which is regulated by the West and Central Pacific Fisheries Commission (WCPFC) Regional Fisheries Management Organization (RFMO).**

Issara Institute indicates that 87% of fishermen in the Thai fishing industry experience significant forms of exploitation and/or trafficking in their work at sea (Issara Institute 2017).

These abuses are hypothesized to be a response to economic and ecological pressures faced by fishing vessels (Tickler et al. 2018a). Fish stocks close to shore are becoming increasingly depleted due to overfishing, *i.e.*, fish continue to be harvested at rates higher than they can replenish themselves. Consequently, fishing vessels must fish further away, into the deep ocean, and for longer periods of time to obtain sufficient catch (Tickler et al. 2018b, Mongabay 2018, Swartz et al. 2010, Pauly et al. 2003, Gianni and Simpson 2009). Tickler et al. (2018a) estimate that it now requires twice the fishing effort of the 1950s to catch the same quantity of fish.

Estimates of fishing labour costs suggest that they comprise 30-50% of total fishing costs (Kelleher et al. 2009, Lam et al. 2011); hence, non-compliance with labor and safety standards or withholding pay can significantly reduce costs for vessel operators. Coupled with long working hours at sea and labor scarcity across the sector, this has resulted in widespread forced labor amounting to modern slavery (Flaim et al. 2018, Issara Institute 2017, Gianni and Simpson 2009). The problem is exacerbated by lack of education for vessel owners (perpetrators) as well as crew members (victims) on the types of labor practices that constitute forced labor, *e.g.*, Flaim et al. (2018) interview vessel owners who openly discuss the use of illegal labor practices without knowing their ramifications.

A by-product of these "distant-water" fishing models is the use of *reefer-to-vessel transshipments* on the high seas. A reefer-to-vessel transshipment (simply referred to as a transshipment hereafter) is the act of offloading fish catch from a fishing vessel to a refrigerated cargo vessel (often called a *reefer*) on the high seas (UN FAO 2011). The cargo vessel would then bring the frozen catch back to port, ensuring that freshly-caught fish does not spoil onboard a fishing vessel that might remain far from shore for months or even years. The cargo vessel would typically also resupply the fishing vessel with fuel and provisions. This practice has obvious economic benefits, allowing fishing vessels to maximize catch as well as minimize fuel costs. Consequently, Asian countries have remained strong proponents of the use of transshipments in the seafood sector (Zimmer 2017).

However, transshipments also significantly reduce transparency in the seafood supply chain by masking where, how, and by whom the fish are caught. Cargo vessels can pick up catch from many fishing boats along their way, enabling them to launder contraband catch into poorly-monitored ports as legally-caught catch. Fig 1 illustrates a common approach to fish laundering in the Pacific Ocean, based on Zimmer (2017). As a result, transshipments are correlated with Illegal, Unreported and Unregulated (IUU) fishing (Kroodsma et al. 2017, Gianni and Simpson 2009).

Critically, transshipments enable fishing vessels to stay at sea for months or even years at a time, which allows fishing vessels to evade monitoring, enforcement and civil society. These conditions pave the way for human rights abuses, *e.g.*, the Issara Institute (2017) finds that physical abuse of fishermen is three times more likely to occur on vessels that transshipped catch in the open ocean.

Amidst these concerns, civil society groups, several UN organizations, NGOs, and marine policy academics have argued that transshipments on the high seas — the open ocean that does not fall within any country's jurisdiction — should be banned entirely (see, *e.g.*, Greenpeace 2016, EJF 2014, UN FAO 2001, UN ODC 2011, Ewell et al. 2017, Gianni and Simpson 2009, Urbina 2015). The challenge is that the high seas are international waters, and so regulations are difficult to enforce since no single country has jurisdiction over these waters. Currently, groups of countries become signatory members to Regional Fisheries Management Organizations (RFMOs) that govern large bodies of international waters — *e.g.*, the West and Central Pacific Fisheries Commission (WCPFC) regulates fishing in the Pacific Ocean— and regulations can only be passed with certain levels of consensus among all signatory members.

In the late 2000s, in response to growing concerns surrounding transshipments on the high seas, several RFMOs instituted a ban on transshipments for certain types of fishing vessels in the waters that they govern — we refer to such bans as *"geographic bans"*. For instance, the WCPFC instituted a ban in 2009 that applied to purse seine vessels in the Pacific Ocean, but not other fishing vessels such as long-lines (Ewell et al. 2017). In fact, proposals to ban transshipments for the long-line fleet were met with dissent from Asian countries for economic reasons (Zimmer 2017).

More recently, pressure has been shifting to seafood buyers to stop sourcing from suppliers that use transshipments at sea, which we refer to as *"supply chain bans."* In response, some major buyers such as Thai Union (parent to the U.S. brand Chicken of the Sea) and Nestle have become early adopters of a moratorium on transshipments at sea throughout their supply chain (Thai Union Group 2017, Nestle 2017). Relatedly, some industry associations pursuing ethical trade have imposed transshipment bans for certain types of vessels or for particular purposes. For example, the International Seafood Sustainability Foundation (ISSF) indicates that their members "shall conduct transactions only with those purse seine vessels that do not engage in transshipments at sea," and the National Fisheries Institute requires senior company officers to sign commitment forms pledging that their "products are not transshipped to avoid duties."

Unfortunately, the widely-held belief among policy-makers, seafood buyers, academics, and the media is that such transshipment bans are ineffective due to limited monitoring and enforcement at sea and at ports (Cullis-Suzuki and Pauly 2010, Zimmer 2017, Gianni and Simpson 2009). First, until very recently[1], there was no systematic way to detect transshipments; thus, vessels could pursue transshipments despite a ban due to lack of oversight (Pintassilgo et al. 2010, O'Leary et al. 2012). Second, while reefer behavior could be monitored remotely because they are required to be equipped with an Automatic Identification System (AIS) transponder, reefers can "go dark" when captains turn off the transponders. It is often unclear if a missing signal is due to poor satellite coverage or strategic behavior by the ship captain, making it difficult to enforce AIS compliance (GFW 2018, Windward 2014). Third, several RFMOs require vessels to report key statistics (*e.g.*, crew size, trip length, catch volume, etc.) in order to determine if any "red flags" are set off (Ewell et al. 2017), but port inspections are particularly weak in certain Southeast Asian countries and other "ports of convenience" (Zimmer 2017, Gianni and Simpson 2009). Fourth, only the flag country — the country where the vessel is registered — can enforce regulations, but an increasing number of vessels are operating under "flags of convenience" that have lax enforcement (Miller and Sumaila 2014, Gianni and Simpson 2009). Fifth, to improve monitoring, several RFMOs began requiring observers on board of a small percentage of fishing vessels; these observers were required to monitor transshipments and report any violations (Ewell et al. 2017). However, there is limited protection for the observer's safety on board the vessel that s/he is tasked to monitor; consequently, observers can easily be bribed, harassed, threatened or obstructed (Zimmer 2017). The WCPFC alone reported 96 instances in a single year where observers were harassed, threatened, or obstructed (WCPFC 2016), and six observers in the Pacific have gone entirely missing (ABC 2017). Finally, the nature of working at sea is such that labor and living conditions are inherently difficult to monitor (Tickler et al. 2018a). Given these monitoring and enforcement challenges, the game-theoretic literature would suggest that a transshipment ban would be ineffective, since vessels can simply ignore the ban (with low probability of getting caught) or strategically evade detection (by going dark, bribing observers, or flying flags of convenience). This belief was reflected in our conversations with key stakeholders, including procurement managers of seafood buyers, marine policy academics, and investigative journalists.

In this paper, we use recent technological developments to monitor vessels' AIS signals (GFW 2018) as well as satellite imagery of fishing pressure (Elvidge et al. 2015) to study vessel behavior in the presence of geographic transshipment bans implemented by RFMOs. We exploit variation over time and across regions to identify the effect of a transshipment ban on detected transshipments, as

[1] Global Fishing Watch's public platform went live in 2016, providing an unprecedented opportunity to track vessels.

well as evasion and strategic behavior of vessels. Surprisingly, despite limited enforcement, we find that bans *are* effective at reducing transshipments by 57%. Unlike popular belief, we find minimal evasive and strategic behavior in response to the ban. Furthermore, we find that this significant reduction comes at a cost of only 3.2% higher landing prices, suggesting that transshipment bans would be an effective tool at combating harm in supply chains while only slightly increasing costs.

The remainder of this paper is structured as follows: §2 describes the datasets, §3 formalizes our hypotheses, and §4 shares our results. We provide concluding remarks in §5.

### 1.1. Contributions

We study the following questions:

1. *Can policies with limited enforcement work?* Does a transshipment ban reduce transshipment rates, despite monitoring and enforcement challenges?

2. *Does evasive or strategic behavior offset any potential benefit of the policy?* Do reefers evade the ban geographically by shifting their transshipments to regions without a ban? Do reefers strategically go dark (turn off AIS) in response to the ban?

3. *Does a ban cause significantly higher raw material costs or change the business model of suppliers?* Does catch from RFMOs with a ban have significantly higher landing prices? Does the ban significantly change fishing activity?

We find that policies with limited enforcement indeed can be effective, and that strategic/evasive behavior in response to this particular policy is minimal. Importantly, the policy does not substantially increase raw material costs at port, circumventing concerns that the policy may aggravate economic pressures. Table 1 summarizes our results and compares them to what one might expect based on economic theory and conversations with key stakeholders in these supply chains.

| | Transshipments | Going dark | Negative spill-overs | Increased Prices |
|---|---|---|---|---|
| Theory | ✗ | ✓ | ✓ | ✗ |
| Empirics | ✓ | ✗ | ✗ | ✓ |

**Table 1 Summary of theoretical versus empirical results about the impact of a ban on key behaviors (transshipment, going dark, negative spill-overs, increased prices).**

We discuss the implications of these results for seafood buyers that consider implementing transshipment bans throughout their supply chains. Directly studying the effect of a supply chain ban is extremely difficult, since it would require intimate knowledge of the commercial relationships between buyers and their suppliers, as well as suppliers and reefers; furthermore, we would require data on this for buyers that did and did not impose a ban. Instead, we show that our findings from the geographic ban provides a conservative estimate of the effect of a supply chain ban. We believe these results can help inform decisions of seafood buyers that are considering following in the footsteps of Thai Union and Nestle to adopt a moratorium on transshipments throughout their supply chains.

### 1.2. Related Literature

Modern-day supply chains rely heavily on low-cost production in developing countries, where governments often lack the capacity or political will to provide protection against environmental and social harm. However, consumers, shareholders, and workers value production that occurs in environmentally and socially responsible ways (Dragusanu et al. 2014, Hainmueller et al. 2015, Burbano 2016, Dyck et al. 2018). Consequently, companies have come to bear financial and reputational burdens when their suppliers engage in noncomplying environmental and labor practices.

Our work relates to a recent literature that empirically studies the efficacy of companies' interventions to change supplier responsibility. Several papers have noted the unintended consequences of limited monitoring and enforcement in these settings. For instance, companies often rely on auditors to ensure responsible supplier behavior; however, Short et al. (2016) use audit data to reveal that reported outcomes are not unbiased, but are rather shaped by a variety of social relationships, institutions, and identities. Thus, heterogeneity in auditor assessment may undermine the efficacy of supplier monitoring and the enforcement of responsible operations. Distelhorst et al. (2015) investigate Hewlett-Packard's supplier responsibility program, and find that national context (not repeated audits, capability building, or supply chain power) is the key predictor of workplace compliance, *e.g.*, factories in China are markedly less compliant than those in countries with stronger civil society and regulatory institutions. Similarly, Toffel et al. (2015) find that suppliers are more likely to adhere to social responsibility standards when they are embedded in states that have stringent domestic labor law and high levels of press freedom. Perhaps as a result, compliance programs promoted by global corporations and nongovernmental organizations have produced only modest and uneven improvements in most global supply chains (Locke et al. 2009).

Yet, in some cases, well-designed interventions have successfully improved supplier compliance. For instance, Harrison and Scorse (2010) find that anti-sweatshop campaigns in Indonesia led to large real wage increases for workers without compromising employment rates in targeted enterprises. Amengual and Chirot (2016) study a leading initiative to improve working conditions in Indonesian garment factories, and find that interventions can be more effective if they seek to improve the effectiveness of existing state institutions, rather than to displace them. Boudreau (2018) performed a randomized controlled experiment demonstrating that worker safety committees can improve labor safety compliance in Bangladeshi garment factories if the factory has good managerial practices. Similarly, our work demonstrates that transshipment bans on the high seas can affect positive change despite limited monitoring and enforcement.

There is also a large literature in socially responsible operations management using analytical models to study buyer interventions towards improving supplier compliance. Chen and Lee (2017) study conditions under which it is optimal to use a combination of screening mechanisms (supplier certification and process audits) and contingency payments to mitigate harm. However, Plambeck and Taylor (2015) show that such measures can actually backfire in the presence of strategic behavior. In particular, if suppliers can successfully evade audits (*e.g.*, as suggested by Short et al. 2016), then interventions can encourage suppliers to exert effort to pass the buyer's audit rather than to prevent environmental or social harm. Another form of backfiring is through reduced transparency; *e.g.* Caro et al. (2018) show that time pressure, price pressure and order complexity can result in reduced transparency in the supply chain through increased unauthorized subcontracting. Our work complements this literature by providing empirical evidence that transshipment bans have a net positive effect in reducing non-compliant supplier behavior, with little to no strategic behavior (geographical evasion) or reduction in transparency (vessels going dark).

Finally, our work belongs to a recent stream of papers leveraging AIS, remote sensing technology and satellite imagery to better understand vessel behavior on the high seas. AIS was originally mandated by the International Maritime Organization in 2000 for collision avoidance, coastal surveillance, and traffic management (Robards et al. 2016). However, more recently, AIS tracking has been viewed as a solution to the challenges of monitoring, control, and surveillance on the high seas, with the ultimate aim of conservation and sustainable use of biodiversity (Dunn et al. 2018). Such knowledge can inform better policy interventions and governance structures to ensure compliant behavior from vessels. For instance, Cabral et al. (2018) use AIS data to study the impact of Indonesia's policies to combat IUU fishing in their Exclusive Economic Zone (EEZ); they find that the policy successfully reduced total fishing effort by foreign-flagged vessels by at least 25%. In contrast, McDermott et al. (2018) show that anticipation of an impending no-take marine reserve policy can actually backfire by triggering an unintended race-to-fish. Thus, AIS can be a useful tool for assessing policy effectiveness, as we do for transshipment bans. Unlike prior work, a key focus of this paper is modeling and quantifying strategic behavior in response to such policies.

Our end goal is to help inform decisions for private seafood buyers (*e.g.*, Thai Union or Nestle) that are considering adopting transshipment bans throughout their supply chains.

## 2. Datasets

This Section describes the multiple data sources that we use in our analyses.

### 2.1. Regional Fisheries Management Organizations (RFMOs) Data

Fisheries on the high seas are managed by 17 RFMOs, which are international bodies comprised of signatory member countries. The number of member countries, as well as the geographic size and number of species managed, differs greatly across RFMOs. In particular, the legal powers of RFMOs are dependent upon the measures and mandates decided by member countries and they vary in strength. However, all RFMOs primarily aim to prevent suspected illegal vessels from entering and landing cargo at ports of member countries or transshipping with member vessels. We obtained spatial data on RFMO borders, as well as RFMO signatory country memberships from the UN FAO's Regional Fishery Bodies Map Viewer (see UN FAO 2018).

We obtained data about the presence of a transshipment ban in each RFMO from Ewell et al. (2017), who manually classified transshipment-related policies in each RFMO by reviewing official documents and websites. In particular, we use the criterion "transshipments prohibited for some vessels," which refers to whether transshipment at-sea is completely prohibited for at least some types of fishing vessels in the RFMO (see Table 8 in the Appendix for the specific vessel types targeted by transshipment bans in each RFMO). Transshipment bans were passed in 6 of 17 total RFMOs in the late 2000s (see Table 2).

| **RFMO** | SEAFO | ICCAT | GFCM | IATTC | IOTC | WCPFC |
|---|---|---|---|---|---|---|
| **Ban implementation year** | 2006 | 2006 | 2007 | 2008 | 2008 | 2009 |

**Table 2 Six of seventeen RFMOs implemented a ban on transshipments on the high seas in the late 2000s.**

### 2.2. Automatic Identification System (AIS) Data

The International Maritime Organization (IMO) requires all international voyaging ships weighing over 300 tons to be equipped with an AIS transceiver, primarily to avoid collisions and promote maritime safety. Reefers typically weigh at least 300 tons, and as a result, 97% of reefers are equipped with AIS transceivers (Miller et al. 2018). This stands in contrast to fishing vessels; only 7% of registered fishing vessels meet the weight criteria and so they are unlikely to be equipped with AIS transceivers. AIS data can therefore reliably be used to study reefer behavior but much less so to study fishing vessel behavior.

AIS transceivers transmit a vessel's unique identifier, position, course and speed every 2 to 3 minutes via VHF radio. Vessels fitted with AIS transceivers can be tracked by AIS base stations located along coast lines or through satellites that are fitted with AIS receivers.

Global Fishing Watch (GFW) was launched in 2016 to monitor global fishing activities by tracking vessels at scale using AIS data collected since 2012. They have publicly released a variety of the resulting pre-processed datasets (see Kroodsma et al. 2018). We obtained data on transshipments and gaps in AIS signals through GFW. We explain these datasets in more detail below.

**Transshipments.** GFW analyzed over 32 billion AIS transmissions from vessels between 2012 and 2017, and identified and tracked 694 unique reefers capable of transshipping at sea and transporting fish. They then used machine learning techniques to identify all locations where these vessels loitered at sea long enough to receive a transshipment, or locations where two vessels (a transshipment vessel and a fishing vessel) were in close proximity long enough to transfer catch, crew or supplies. The resulting 46,570 events were labeled as "loitering events," which signal likely transshipments (see the data release paper, Miller et al. 2018, for additional details). We henceforth refer to these loitering events as detected transshipments.

We performed two key pre-processing steps. First, since we are interested in transshipments on the high seas, we exclude transshipments that occurred within Exclusive Economic Zone (EEZ). EEZs are areas in the ocean that typically stretch out 200 nautical miles from a country's coastline; countries have special rights to fish in these zones as prescribed by the UN Convention on the Law of the Sea. We obtained EEZ boundaries from Marine Regions (2018). Second, not all transshipments are illegal, even in regions with a ban. In particular, vessels can receive prior authorization to transship. The Western & Central Pacific Fisheries Commission publishes a list of vessels that are authorized to transship in areas governed by RFMOs (see WCPFC 2018). Authorization periods start in 2008 and sometimes go until 2023. We exclude 1,079 transshipments involving reefers that were authorized to transship at the time of the event.

Fig. 2 plots unauthorized transshipments on the high seas over time. Transshipments in locations with (without) a transshipment ban are shown in orange (blue). The trend lines suggest that transshipments are steeply increasing in regions without a transshipment ban, and only mildly increasing in regions with a ban.

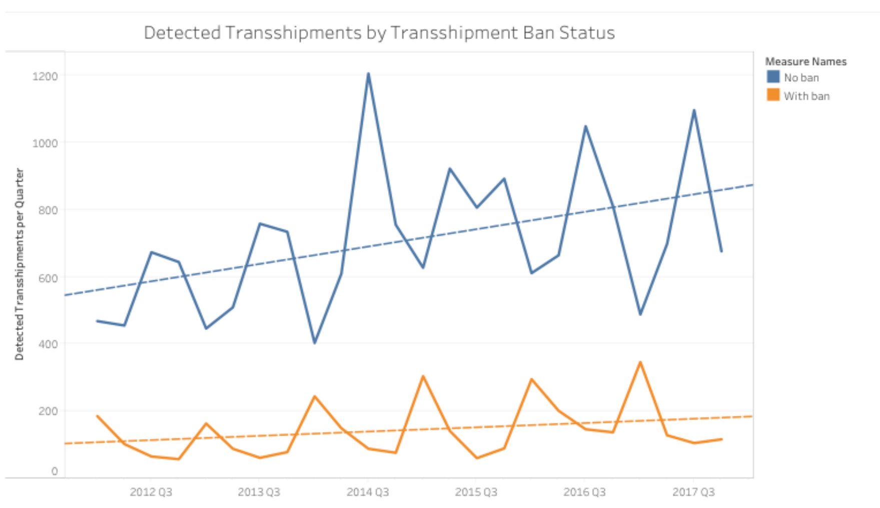


**Figure 2 Detected non-authorized transshipments on the high seas over time, in regions where a transshipment ban is in effect (orange) and where no ban is in effect (blue). Dashed lines represent the best linear trend fit.**

Next, Fig. 3 shows the location of unauthorized transshipments on the high seas. EEZ borders are depicted by grey lines, ocean regions that are part of an RFMO with no transshipment ban (between 2012 and 2017) are shaded light blue, and remaining ocean regions are shaded dark blue.

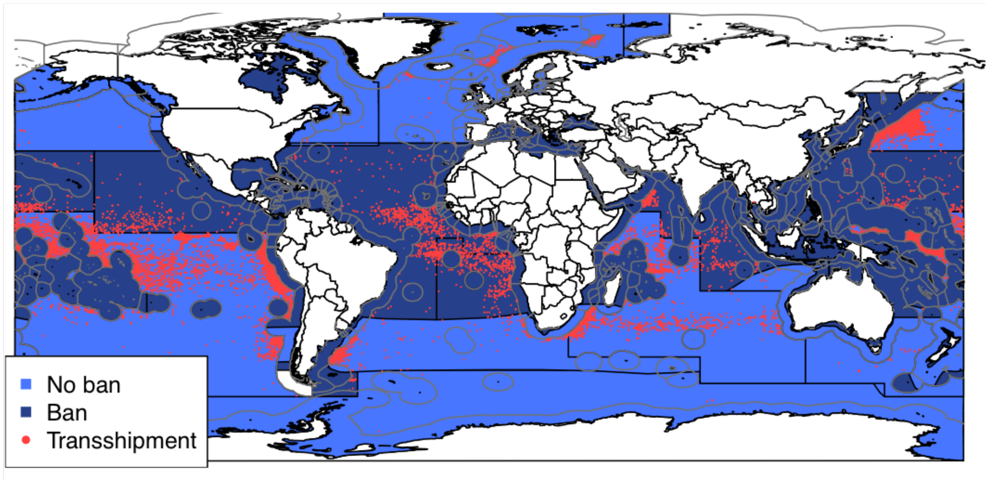


**Figure 3** RFMO regions with a partial ban or no partial ban, overlaid with transshipments (2012-2017). Grey lines indicate boundaries of Exclusive Economic Zones (EEZ).

**Gaps in AIS signals.** Vessels may "go dark" at sea due to a gap in AIS signals. Such a gap may occur when the vessel operator turns off its AIS transceiver for a period of time, or because there was poor satellite coverage at that time and location. The first is illegal strategic behavior, while the second is a natural cause, and it is currently not possible to tell the difference. We obtained a database of gaps in AIS signals from GFW, which allows us to observe the position of the vessel when it lost and re-gained coverage. We will use this data to assess the extent to which vessels strategically go dark.

It is common for vessels to have small gaps in their AIS signals due to poor satellite coverage. However, a vessel needs to go dark for at least several hours to perform a transshipment entirely in the "dark." Fig. 9 in the Appendix shows a histogram of the duration of transshipments, indicating that 99% of transshipments last for 4.75 hours or more. Thus, we restrict our analyses to AIS gaps of at least 4.75 hours on the high seas.

We may also be concerned about how strategic behavior could bias the trends we observe in Fig. 2. When vessels strategically go dark during a transshipment, these transshipments will namely not be captured in the detected transshipments. Fig. 4 shows the time trend for gaps in AIS signals, in RFMOs with and without a transshipment ban. These trends are fairly robust to the choice of gap length (see Fig. 10 in the Appendix). The trends suggest that gaps in AIS signals are decreasing, which contrasts with transshipments that are increasing (see Fig. 2)

### 2.3. Spatial Fishing Activity Data

The AIS data allows us to reliably understand the behavior of reefers, but as discussed earlier, fishing vessels are often too small to be equipped with AIS transceivers. However, recent remote sensing technology allow us to study fishing *activity* from space. The Visible Infrared Imaging

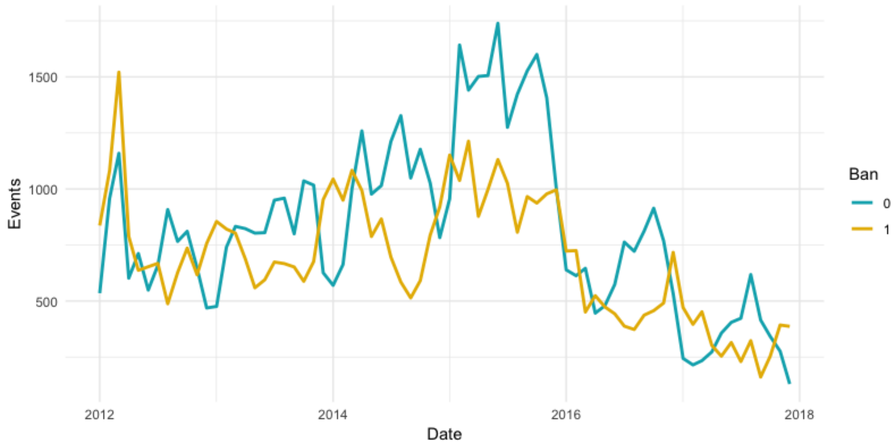


**Figure 4** **Events where a vessel went dark during at least 4.75 hours, in RFMOs with (yellow) and without (blue) transshipment ban.**

Radiometer Suite (VIIRS) day/night band on the the Suomi National Polar Partnership satellite collects low light satellite images at night. Elvidge et al. (2015) pre-processed these images to detect lit fishing boats at night. This allows us to detect fishing vessel presence, but does not allow us to assign a unique identifier to the boat. We use this data to analyze relative fishing activity over time in regions with and without transshipment bans. Fig. 5 shows the density of VIIRS-detected boats in Asia in 2016. Our analyses are restricted to the Asia region from 2012-2016 depicted in Fig. 5 because this is the only region for which data was consistently available over time.

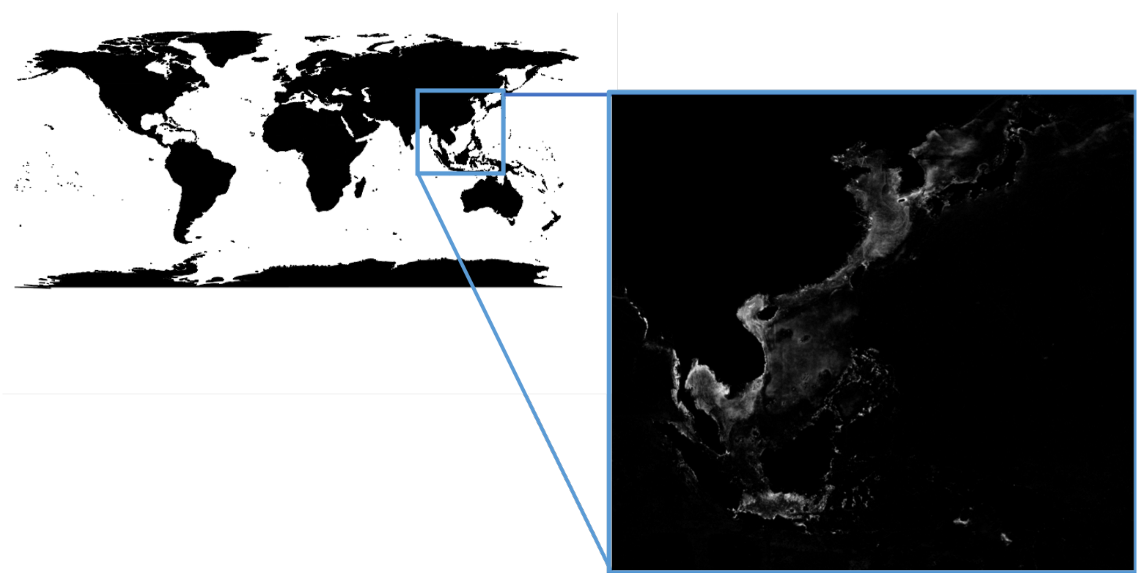

**Figure 5** **VIIRS-based boat detection in Asia in 2016.**

### 2.4. Landing Price Data

We obtained a database of the volumes and value of fish landings for each RFMO over time for different fish species from the Sea Around Us project (Daniel and Zeller 2015). We compute average landing prices by dividing the total landing value by total landing volume; the detailed methodology behind the data construction is reported in Cullis-Suzuki and Pauly (2010). We consider prices by RFMO across 30 different functional groups (based on fish species and size of catch) over the years 2000-2014. Importantly, unlike the satellite datasets discussed so far, this data allows us to study prices both before and after the implementation of transshipment bans. Fig. 6 shows the median price per ton of catch across functional groups and RFMOs with (orange) and without (blue) a transshipment ban. The grey shaded area represents the years during which transshipment bans went into effect for RFMOs that implemented them. The trends suggest that catch prices were very similar across RFMOs before the implementation of bans; however, after implementation, RFMOs with a transshipment ban have higher median landing prices.

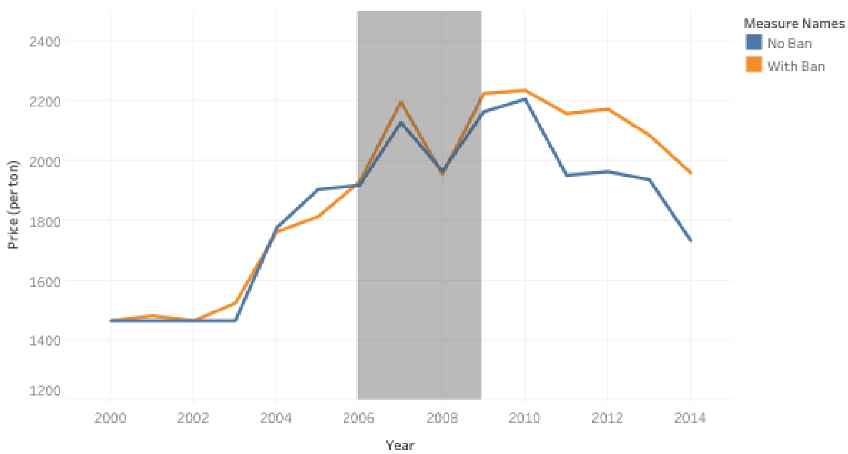


**Figure 6 The median price per ton of catch across RFMOs without (blue) and with (orange) a transshipment ban. RFMOs implemented transshipment bans during the year range 2006-2009 (shaded area).**

## 3. Hypotheses

This Section develops a simple model to formalize our hypotheses regarding the effect of a geographic ban on vessel behavior and supply chain costs. Specifically, we formalize hypotheses regarding the effect of the ban on (1) transshipments, (2) geographical evasion, (3) vessels strategically "going dark", and (4) fishing activity and landing prices. Finally, we argue that findings from the geographic ban provide a conservative estimate of the effect of a supply chain ban.

### 3.1. Transshipments

Let $\ell$ be a location on the high seas, $B \in \{0,1\}$ be an indicator variable for the presence of a ban, and $Y$ be the year (*i.e.*, time). The number of transshipments $T(\ell, Y, B)$ is a function of the location, the year, and the presence of a ban. In particular, the number of detected transshipments may depend on the location due to environmental conditions that make a location ideal for fishing or transshipment, or due to location-dependent satellite coverage. This makes it difficult to study the effect of ban status on the *number of transshipments* unless we can control for the effect of location. We therefore instead study the impact of ban status on the yearly *change in transshipment rates* for any given location. This quantity can be written as

$$C^T(\ell, Y, B) \;\equiv\; \frac{1}{T(\ell, Y, B)} \cdot \frac{dT(\ell, Y, B)}{dY} \;=\; \frac{d \log T(\ell, Y, B)}{dY}\,.$$

We consider the following hypothesis: *the growth in transshipment rates over time is lower with a ban than without a ban.* Here, we assume that detected transshipments are an unbiased estimate of actual transshipments; we relax this assumption in §3.3, where we consider reefers that go dark. Mathematically, this hypothesis corresponds to the following null hypothesis $H_0^{(t)}$, and corresponding alternative hypothesis $H_1^{(t)}$ on transshipment rates:

$$H_0^{(t)}:\; C^T(\ell, Y, 0) \;\leq\; C^T(\ell, Y, 1) \qquad \text{and} \qquad H_1^{(t)}:\; C^T(\ell, Y, 0) \;>\; C^T(\ell, Y, 1)\,. \tag{1}$$

We empirically test this hypothesis in §4.1.

Performing this regression on observational data may be problematic if the ban is an endogenous variable, *e.g.,* the ban was passed in regions where transshipment rates were already decreasing over time. A standard differences-in-differences analysis is infeasible in this context because data prior to the enactment of transshipment bans is unavailable — data on detected transshipments only exists for years after 2012, but no new geographic bans have been enacted since 2009. We therefore use instrumental variables and a threshold model to alleviate endogeneity concerns.

**Instrumental variable approach.** Our instruments are national personal income and sales tax rates averaged across member countries of an RFMO. We obtained country-level tax data from `https://tradingeconomics.com/`. Higher tax rates typically signify stronger government regulation and enforcement. We find that RFMOs with member countries that have higher tax rates are less likely to institute a transshipment ban. However, the personal income and sales tax rates of member countries are unlikely to have a direct relationship with (i) the unobserved variations in environmental factors or fishing patterns that make transshipments more or less necessary in certain RFMOs, or (ii) the outcome of transshipment rates on the high seas. Thus, we argue that our instruments satisfy the exclusion restriction.

**Threshold model.** We provide additional evidence that a transshipment ban *causes* changes in transshipment behavior by studying transshipment behavior at RFMO borders. Looking at the map in Fig. 3, we see that nearly all borders between regions with and without a ban coincide with an EEZ. However, there is a significant stretch near the equator on the Pacific Ocean, where there is an uninterrupted border between regions with and without a transshipment ban. Note that the environmental factors, fishing patterns and satellite coverage are exactly the same for a short distance on either side of the border. Thus, focusing on this region, significant differences in transshipment rates on either side of the border can almost certainly be attributed to the transshipment ban. Note that this approach can only estimate a localized treatment effect near the RFMO border, and cannot provide counterfactuals for ban adoption across the high seas. However, it can provide compelling additional evidence for the existence of an effect.

### 3.2. Geographical Evasion

In response to a geographic transshipment ban, a reefer could either not tranship or evade the ban by transshipping in regions without a ban. Transshipments could therefore decrease or shift to regions without a ban. Either response would lead to a finding of reduced transshipment rates in regions with a ban relative to regions without a ban. However, they yield very different conclusions; if vessels are simply geographically evading the ban, it is unclear whether harm was reduced, and whether these results can inform the success of a supply chain ban (see §3.5).

Under geographical evasion, transshipments that were originally intended to occur in regions with a ban would shift across an RFMO border to a region without a ban. These vessels naturally would prefer to travel shorter distances, and so the resulting transshipments are likely to occur closer to the RFMO border; clearly, this would change the distribution of transshipments in regions with no ban. Thus, conditioning on finding reduced transshipment rates in regions with a ban (*i.e.,* $H_1^{(t)}$ from the previous section), we argue the following: in the presence of geographic evasion, we would observe an increasing transshipment rate near RFMO borders in regions without a ban.

Let $D(\ell)$ denote the *shortest* distance between a transshipment in a location $\ell$ with no ban, and any location with a ban. Note that $D(\ell)$ is positive and finite for all locations $\ell$ without a ban. We consider the following hypothesis: *considering all locations $\ell$ in regions without a ban, the growth in transshipment rates over time is higher in locations that are closer to regions with a ban.* Mathematically, this corresponds to the following null hypothesis $H_0^{(e)}$, and corresponding alternative hypothesis $H_1^{(e)}$ on geographic evasion:

$$H_0^{(e)}: \frac{dC^T(\ell, Y, 0)}{dD(\ell)} \geq 0 \quad \text{and} \quad H_1^{(e)}: \frac{dC^T(\ell, Y, 0)}{dD(\ell)} < 0. \tag{2}$$

We empirically test this hypothesis in §4.2.

### 3.3. Dark Vessels

Thus far, we have discussed *detected* transshipments. However, vessel operators can strategically turn off their AIS transponders and "go dark" while performing a transshipment. Such transshipments will not be captured in our dataset of detected transshipments; instead, we would detect a gap in AIS signals. We examine the length of gaps that are long enough to potentially conduct a transshipment, *i.e.,* 4.75 hours or greater based on Fig. 9 in the Appendix. Henceforth, we refer to AIS gaps as gaps in AIS signals of at least 4.75 hours.

Conditioning on finding reduced transshipment rates in regions with a ban (*i.e.,* $H_1^{(t)}$), we then argue the following: in the presence of strategic dark behavior, we would observe an increasing rate of AIS gaps in regions with a ban. (We note that satellite coverage of AIS signals did not change during the years considered in our analysis.) To be more precise, let $G(\ell, Y, B)$ be the number of AIS gaps by reefers as a function of location $\ell$, year $Y$ and ban status $B$. Let $C^G(\ell, Y, B)$ denote the associated yearly change in AIS gap rates,

$$C^G(\ell, Y, B) \equiv \frac{1}{G(\ell, Y, B)} \cdot \frac{dG(\ell, Y, B)}{dY} = \frac{d \log G(\ell, Y, B)}{dY}.$$

We consider the following hypothesis: *the growth in AIS gap rates is greater with a ban that without a ban.* Mathematically, this corresponds to the following null hypothesis $H_0^{(d)}$, and corresponding alternative hypothesis $H_1^{(d)}$ on AIS gap rates:

$$H_0^{(d)}: C^G(\ell, Y, 0) \geq C^G(\ell, Y, 1) \quad \text{and} \quad H_1^{(d)}: C^G(\ell, Y, 0) < C^G(\ell, Y, 1). \tag{3}$$

We empirically test this hypothesis in §4.3.

### 3.4. Economic Analysis

Transshipments are a cornerstone of the fishing business model that emerged in response to growing economic pressures in the seafood sector. The same economic pressures are also hypothesized to be a key driver behind increasing environmental and social harm. Two relevant questions are therefore whether a change in transshipments is associated with a change in the fishing business model, and whether a change in transshipments is associated with a change in fishing costs. We formalize these two questions next.

**Fishing business model.** Because transshipments primarily serve to offload frozen catch from fishing vessels, we expect that transshipments scale linearly with fishing activity. Thus, if a change in transshipments is associated with a significant change in the fishing business model, we would expect that changes in transshipment rates differ significantly from changes in fishing activity.

Let $F(\ell, Y, B)$ be the fishing activity in location $\ell$, year $Y$ and ban status $B$, and let $C^F(\ell, Y, B)$ denote the associated yearly change in fishing activity,

$$C^F(\ell, Y, B) \equiv \frac{1}{F(\ell, Y, B)} \cdot \frac{F(\ell, Y, B)}{dY} = \frac{d \log F(\ell, Y, B)}{dY}.$$

We are interested in the normalized transshipment rate per unit of fishing activity,

$$\frac{dT/T}{dF/F} = \frac{d\log T/dY}{d\log F/dY} = \frac{C^T(\ell, Y, B)}{C^F(\ell, Y, B)}.$$

We consider the following hypothesis: *the normalized transshipment rate per unit of fishing activity is significantly different with a ban than without a ban.* Mathematically, this corresponds to the following null hypothesis $H_0^{(f)}$, and corresponding alternative hypothesis $H_1^{(f)}$ on fishing activity:

$$H_0^{(f)}: \frac{C^T(\ell, Y, 0)}{C^F(\ell, Y, 0)} = \frac{C^T(\ell, Y, 1)}{C^F(\ell, Y, 1)} \quad \text{and} \quad H_1^{(f)}: \frac{C^T(\ell, Y, 0)}{C^F(\ell, Y, 0)} \neq \frac{C^T(\ell, Y, 1)}{C^F(\ell, Y, 1)}. \tag{4}$$

We empirically test this hypothesis in §4.4.

**Landing Prices.** If a change in transshipments is associated with a significant change in fishing costs, we would expect these costs to be passed down — at least to some extent — to landing prices of fish. We use time series data on landing prices by fish species and RFMO to study how prices have changed before and after the ban.

Let $P(S, R, Y, B)$ denote the median per-unit landing price for fish belonging to functional group $S$ (size and species), caught in RFMO $R$, in year $Y$, as a function of the ban status $B$. We consider the following hypothesis: *landing prices for fish catch are significantly different when caught in a region with a ban than without a ban.* Mathematically, this corresponds to the following null hypothesis $H_0^{(p)}$, and corresponding alternative hypothesis $H_1^{(p)}$ on landing prices:

$$H_0^{(p)}: P(S, R, Y, 0) \neq P(S, R, Y, 1) \quad \text{and} \quad H_1^{(p)}: P(S, R, Y, 0) = P(S, R, Y, 1). \tag{5}$$

We empirically test this hypothesis in §4.4. Because the ban status $B$ is a function of the RFMO $R$ and the year $Y$ in our observational data, we use a differences-in-differences approach to disentangle the treatment effect from differential price trends across regions with and without a ban.

### 3.5. Supply Chain Ban

Thus far, we have focused on assessing the impact of *geographic* transshipment bans by RFMOs. We now derive conditions under which these results can inform a *supply chain* ban by buyers.

First, we note that geographical evasion could pose a key difference between the two types of bans. In particular, reefers can choose between complying with the policy or transshipping (either visibly or by going dark) under both bans; however, reefers can additionally choose to geographically evade the ban under a geographic ban. Nevertheless, in §4.2, we show empirically that there is no significant geographical evasion under the geographic ban. Thus, the choices faced by reefers are the same for both types of bans.

Next, the rewards and penalties of each action may be different under the two types of bans. In particular, let the type of ban $I \in \{G, S\}$ denote the implementation of geographic ($G$) and supply chain ($S$) ban respectively, and let the type of violation $V \in \{T, D\}$ denote transshipments (violations of the ban) that are conducted while the vessel's AIS transponder is on ($T$) and off ($D$) respectively. For a given ban type $I$ and violation $V$, reefers incur a penalty $p_I$ if they are caught, which occurs with probability $\pi_I^V$. The penalty $p_G$ for a geographic ban could be losing access to dock at a preferred port, while the penalty $p_S$ for a supply chain ban could be losing the opportunity to supply to a preferred buyer. In the case of dark transshipments ($V = D$), vessels can incur an additional penalty if they collude, but this penalty is independent of the type of ban. When the *expected* penalties for the supply chain ban are higher than those for a geographic ban, our results for geographical evasion can provide a conservative estimate of the success of a transshipment ban. In other words, we require

$$p_S \pi_S^T \;\geq\; p_G \pi_G^T \qquad \text{and} \qquad p_S \pi_S^D \;\geq\; p_G \pi_G^D \,.$$

Critically, the buyer can always enforce this inequality by choosing appropriate probabilities $\pi_S^T$ and $\pi_S^D$ of being caught (*e.g.,* through auditing) such that $p_G/p_S \leq \min\{\pi_S^T/\pi_G^T, \pi_S^D/\pi_G^D\}$. Note that if enforcement and monitoring is poor under a geographic ban, as seems to be the case, then $\pi_G^T$ and $\pi_G^D$ are small and therefore the required $\pi_S^T$ and $\pi_S^T$ are likely to be small as well.

## 4. Results

We conduct a standard grid-cell level analysis by partitioning the high seas into discrete smaller regions. Our grid cells are $0.5 \times 0.5$ degrees in latitude and longitude for all the following analyses. This gives us a total of 5,531 grid cells, where 1,501 cells are under a transshipment ban and 3,730 cells are not. Note that grid cells in the same RFMO may have correlated heteroskedastic errors due to unobserved RFMO-specific variables. To account for this, we use cluster-robust standard errors (clustered at the RFMO level) in all regressions to allow both arbitrary heteroskedasticity and arbitrary within-RFMO correlation.

### 4.1. Transshipments

We define the yearly change in transshipment rates in location $\ell$ and year $y$ as

$$C_{\ell,y}^T \equiv \frac{T(\ell,y) - T(\ell,y-1)}{T(\ell,y-1)} \,.$$

To test hypothesis (1), we use a linear model with the econometric specification

$$C_{\ell,y}^T = \beta_t B_\ell + \overline{\beta}_{FE} \overline{Y} + \varepsilon_{\ell,y} \,,$$

where $B_\ell$ is the presence of a ban in location $\ell$ (our treatment variable), the vector $\overline{Y}$ contains yearly fixed effect dummies, and $\varepsilon_{\ell,y}$ is the error term. The coefficient of interest is $\beta_t$, which represents the effect of a transshipment ban on the yearly change in transshipment rates. Specifically, if $\beta_t$ is negative, this would indicate that transshipment rates are growing relatively less slowly in regions with a transshipment ban.

We also perform an instrumental variable version of the above regression to account for potential endogeneity of transshipment ban adoption. We use standard two-stage least squares for estimation using the ivreg2 Stata package. In the first stage, we fit our endogenous variable

$$B_\ell = \overline{\beta}^0_{FE}\overline{Y} + \varepsilon^0_{\ell,y}\,,$$

In the second stage, we fit our outcome variable using the predicted $B_\ell$ from the first stage,

$$C^T_{\ell,y} = \beta_t\hat{B}_\ell + \overline{\beta}_{FE}\overline{Y} + \varepsilon_{\ell,y}\,.$$

The results for both regressions are shown in Table 3.

Outcome: Yearly Change in Loitering Rate

| **Variable** | **(1) Regression** | | **(2) 2-SLS IV Regression** | |
|---|---|---|---|---|
| | **Estimate** | **Std Error** | **Estimate** | **Std Error** |
| (Intercept) | 0.85** | 0.12 | 0.85** | 0.10 |
| Is 2014 | 0.64** | 0.18 | 0.64** | 0.17 |
| Is 2015 | −0.10 | 0.30 | −0.10 | 0.28 |
| Is 2016 | −0.25 | 0.18 | −0.25 | 0.17 |
| Is 2017 | −0.11 | 0.16 | −0.11 | 0.14 |
| **Ban** | **− 0.57**** | **0.16** | **−0.58**** | **0.17** |

$^*p < 0.05$, $^{**}p < 0.01$

**Table 3 Regression and 2-SLS IV regression results with cluster-robust standard errors for yearly change in detected transshipments per grid cell as a function of transshipment ban status.**

We find extremely similar treatment effects in both the instrumented and non-instrumented regressions. The presence of a transshipment ban reduces transshipment rates in a given location by 57% a year under the non-instrumented regression, and 58% a year under the instrumented regression. It is important to note that this reduction is *relative* to transshipment rates in a location without a ban. In fact, the general trend shows increasing transshipment rates over time in regions with and without a transshipment ban, since the coefficient of the intercept term in Table 3 is positive and larger in magnitude than the treatment coefficient $\beta_t$. In other words, transshipment bans appear to successfully dampen the increase in transshipment rates, but do not eliminate it. These results match the trends we observed in Fig. 2.

We performed the standard IV validity tests under robust RFMO-level clustering. First, we performed a weak identification test, yielding a Craag-Donald Wald $F$-statistic of 438. This is well above the Stock-Yogo weak ID test critical values for the maximal IV size (19.93 at the 10% level), indicating that our instruments are not weak. Second, we performed an overidentification test, yielding a Hansen J statistic of 1.93 with a $\chi^2$ $p$-value 0.16. Thus, we do not reject the null hypothesis that our model is correctly specified, suggesting that our instruments are valid, *i.e.,* national personal income and sales tax rates are uncorrelated with the change in transshipment rates except through the treatment variable and yearly fixed effects. Third, we checked for endogeneity of the treatment variable, and do not reject the null hypothesis ($p = 0.38$) that the treatment variable is exogenous. This suggests that the transshipment ban may not be endogeneous, which matches our finding of similar treatment effects for both the instrumented and non-instrumented regressions.

Next, we provide additional evidence that transshipment bans *cause* changes in transshipment behavior by examining transshipment rates at the RFMO border. Looking at the map in Fig. 3, we see that nearly all borders between regions with and without a ban coincide with an EEZ. However, there is a significant stretch near the equator on the Pacific Ocean, where there is an uninterrupted border between regions with and without a transshipment ban. As shown in Fig. 7, we manually construct 34 grid cells along this border, each with an area of $50,000$ squared kilometers on either side of the border. Areas along the border where the border is too close to an EEZ (grey lines) or where there are no transshipment events on either side are not included.

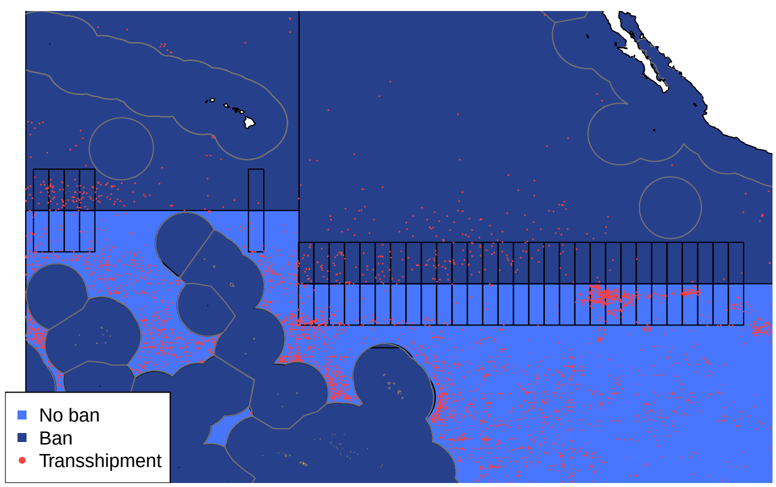


**Figure 7 RFMO border on the Pacific Ocean. Regions with and without a transshipment ban are shaded dark and light blue respectively. Rectangles show 34 grid cells with equal area on either side of the border.**

As discussed earlier, the environmental factors, fishing patterns and satellite coverage are exactly the same on either side of the border within a grid cell. Thus, significant differences in transshipment rates within a grid cell on either side of the border can almost certainly be attributed to the transshipment ban. We find an average of 5.1 transshipments per grid cell in the ban region, and

15.4 transshipments in the no-ban region. A paired one-sided $t$-test reveals that this difference is statistically significant with a $p$-value of 0.02. Thus, the ban indeed appears to cause a (local) reduction in transshipments, which is consistent with our earlier regression results. This may either be through (i) a reduction in transshipment rates in regions with a ban, and/or (ii) a shift in transshipments from regions with a ban to regions without a ban. We explore the second hypothesis in the next subsection.

### 4.2. Geographical Evasion

To test hypothesis (2), we use a linear model with the econometric specification

$$C^T_{\ell,y} = \beta_e D_\ell + \overline{\beta}_{FE}\overline{Y} + \varepsilon_{\ell,y}\,,$$

where our locations $\ell$ are grid cells with no transshipment ban, and $D_\ell$ is the *shortest* distance between the center of the grid cell $\ell$ and any point on the high seas with a transshipment ban. The vector $\overline{Y}$ contains yearly fixed effect dummies, and $\varepsilon_{\ell,y}$ is the error term. The coefficient of interest is $\beta_e$, which represents the effect of distance from a RFMO border on the yearly change in transshipment rates. Specifically, if $\beta_e$ is negative, this would indicate geographic evasion, *i.e.,* vessels may be moving across RFMO borders to regions with no ban to perform a transshipment. The results are shown in Table 4.

Outcome: Yearly Change in Detected Transshipment Rates

| **Variable** | **Estimate** | **Std Error** |
|---|---|---|
| (Intercept) | 0.96** | 0.08 |
| Is 2014 | 0.69** | 0.20 |
| Is 2015 | −0.14 | 0.34 |
| Is 2016 | −0.24 | 0.22 |
| Is 2017 | −0.16 | 0.16 |
| **Distance** | **−0.01** | **0.01** |

*$p < 0.05$, **$p < 0.01$

**Table 4 Regression results with cluster-robust standard errors for yearly change in transshipment rates per grid cell (without a ban) as a function of distance to the closest point on the high seas with a ban.**

While the point estimate of $\beta_e$ is negative, it is small in magnitude and is not statistically significant. Thus, we do not find significant evidence for geographic evasion, and cannot reject $H_0^{(e)}$.

Alternatively, one might argue that the effect of distance may not be linear in distance. In particular, transshipments that were originally intended to occur in regions with a ban would only shift a *short* distance across a RFMO border to a region without a ban. As a result, we may only see an effect in a narrow band around the border (similar to our threshold model results in §4.1).

Thus, we perform the same regression, but restricted to locations $\ell$ that are at most some distance $d$ from the border, on both sides of the border, *i.e.* we estimate:

$$C^T_{\ell,y} = \beta^1_{e,d} D^1_\ell + \overline{\beta}^1_{FE} \overline{Y} + \varepsilon^1_{\ell,y},$$
$$C^T_{\ell,y} = \beta^2_{e,d} D^2_\ell + \overline{\beta}^2_{FE} \overline{Y} + \varepsilon^2_{\ell,y},$$

where $D^1_\ell$ is the shortest distance between the center of grid cell $\ell$ in a region without a ban and any point on the high seas with a ban; analogously $D^2_\ell$ is the shortest distance between the center of grid cell $\ell$ in a region with a ban and any point on the high seas without a ban. Note that we only consider grid cells $\ell$ within a distance $D^1_\ell, D^2_\ell \leq d$ of the border.

Fig. 8 shows the difference $\beta^1_{e,d} - \beta^2_{e,d}$ for each $d$. If there was evasion, then the slope would be more negative for transshipments in no-ban areas, and the difference should therefore be negative.

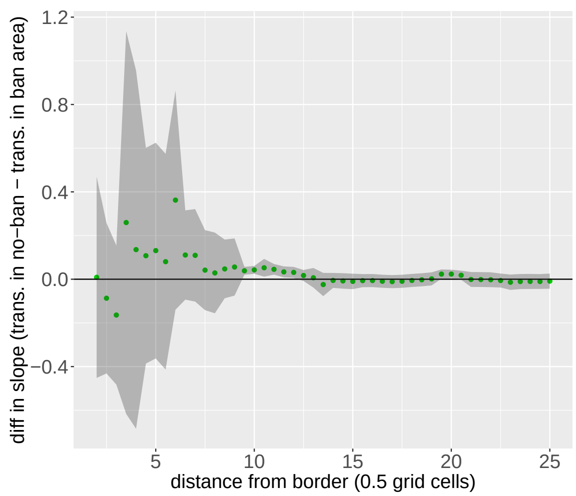


**Figure 8 Difference in regression coefficients $\beta^1_{e,d} - \beta^2_{e,d}$ as a function of distance $d$ from the border. 95% confidence intervals are computed using cluster-robust standard errors.**

First, note that the difference in coefficients is 0 for large values of $d$ on either side of the border, *i.e.,* yearly changes in transshipment rates are uncorrelated with the location of RFMO borders. This suggests that geographic evasion is minimal, matching our regression results in Table 4. For smaller values of $d$, we see a statistically insignificant negative value of the difference in coefficients, suggesting that there is no significant geographical evasion near the border. Together, these results indicate that geographical evasion in response to the transshipment ban is minimal. We hypothesize that this may be because transshipments often occur far from RFMO borders (see Fig. 2), and it may therefore not be economically worthwhile to voyage to a border to evade a potential penalty. In fact, for our threshold model in §4.1, we were only able to find one uninterrupted border (between regions with and without a transshipment ban) with a sufficient number of transshipments (Fig. 7).

### 4.3. Dark Vessels

As discussed in our hypotheses, we begin by defining the yearly change in AIS gap rates (gaps at least 4.75 hours long) in location $\ell$ and year $y$ as

$$C^G_{\ell,y} \equiv \frac{G(\ell,y) - G(\ell,y-1)}{G(\ell,y-1)} .$$

To test hypothesis (3), we use a linear model with econometric specification

$$C^G_{\ell,y} = \beta_d B_\ell + \overline{\beta}_{FE}\overline{Y} + \varepsilon_{\ell,y} ,$$

where $B_\ell$ is the presence of a ban in location $\ell$, the vector $\overline{Y}$ contains yearly fixed effect dummies, and $\varepsilon_{\ell,y}$ is the error term. The coefficient of interest is $\beta_d$, which represents the effect of a transshipment ban on the yearly change in AIS gap rates. Specifically, if $\beta_d$ is positive, this would indicate that vessels are going dark at an increasing rate in regions with a transshipment ban. We can perform this regression in two ways. We can take $\ell$ to be the location of the vessel at the time when it went dark (*i.e.,* the location at the start of the AIS gap); alternatively, we can take $\ell$ to be the location of the vessel at the time when it stopped being dark (*i.e.,* the location at the end of the AIS gap). The results for both regressions are show in Table 5.

We find that $\beta_d$ is, in fact, significantly negative; the presence of a transshipment ban reduces AIS gap rates in a given location by 28–29% a year, depending on whether we use the starting or ending location of the vessel. Table 9 in the Appendix shows results of the same two regressions with AIS gaps that are longer than 7.5 hours (the median length of a detected transshipment); the presence of a ban then significantly reduces AIS gap rates in a given location by 31% a year compared to grid cells without a ban, when using either the starting or ending location of the vessel. Thus, we do not find significant evidence for strategic dark behavior, and cannot reject $H_0^{(d)}$.

Outcome: Yearly Change in AIS Gap Rate

| **Variable** | **(1) Location at Start of Gap** | | **(2) Location at End of Gap** | |
|---|---|---|---|---|
| | **Estimate** | **Std Error** | **Estimate** | **Std Error** |
| (Intercept) | 0.54** | 0.13 | 0.60** | 0.16 |
| Is 2014 | 0.02 | 0.08 | −0.02 | 0.09 |
| Is 2015 | 0.10 | 0.09 | 0.04 | 0.11 |
| Is 2016 | −0.31** | 0.09 | −0.33** | 0.10 |
| Is 2017 | −0.23 | 0.14 | −0.32 | 0.17 |
| **Ban** | **−0.28**** | **0.10** | **−0.29**** | **0.11** |

$^*p < 0.05$, $^{**}p < 0.01$

**Table 5 Regression results with cluster-robust standard errors for yearly change in AIS gap rates per starting grid cell (left) or ending grid cell (right) as a function of transshipment ban status.**

### 4.4. Economic Analysis

**Fishing Activity.** We use VIIRS satellite images in the Asia region (see Fig. 5) to study the time trend of fishing activity in regions with and without a transshipment ban. To test hypothesis (4), we use a linear model with econometric specification

$$C^F_{\ell,y} = \beta_f B_\ell + \overline{\beta}_{FE}\overline{Y} + \varepsilon_{\ell,y} \,,$$

where $B_\ell$ is the presence of a ban in location $\ell$, the vector $\overline{Y}$ contains yearly fixed effect dummies, and $\varepsilon_{\ell,y}$ is the error term as before. The coefficient of interest is $\beta_f$, which represents the effect of a transshipment ban on the yearly change in fishing activity. Specifically, if $\beta_f$ is negative, this would indicate that fishing pressure is growing relatively less slowly in regions with a transshipment ban. The results are shown in Table 6.

Outcome: Yearly Change in Fishing Activity

| **Variable** | **Estimate** | **Std Error** |
|---|---|---|
| (Intercept) | 0.15** | 0.01 |
| Is 2014 | 0.14** | 0.01 |
| Is 2015 | 0.16** | 0.01 |
| Is 2016 | 0.03 | 0.01 |
| **Ban** | **−0.06**** | **0.01** |

*$p < 0.05$, **$p < 0.01$

**Table 6** **Regression results with cluster-robust standard errors for yearly change in fishing activity per grid cell as a function of transshipment ban status.**

We find that the presence of a transshipment ban reduces fishing activity by 6% a year. Note that this reduction is *relative* to fishing activity in locations without a ban. In fact, the general trend shows increasing fishing activity over time in regions with and without a ban, since the coefficient of the intercept term in Table 6 is positive and larger in magnitude than the treatment coefficient $\beta_f$. In other words, transshipment bans only appear to dampen increasing fishing activity on the high seas, but do not eliminate it.

These results suggest that concerns that the ban may raise fishing vessel costs and therefore reduce fishing activity may be well-founded. However, the 6% reduction in fishing activity is far smaller than the 57% reduction in transshipment rates we found earlier. Returning to hypothesis (4), a simple computation yields that the normalized transshipment rate per unit of fishing pressure is 5.7 in regions without a ban and 3.1 in regions with a ban; this difference is statistically significant, rejecting $H_0^{(f)}$. This suggests that the ban significantly changed fishing models on the high seas.

**Landing Prices.** We use landing prices of fish catch (see Fig 6) to study the time trend of prices in regions with and without a transshipment ban. Recall that $P_{s,r,y}$ is the median landing price of catch in functional group $s$ in RFMO $r$ and year $y$. To test hypothesis (5), we use a linear model with econometric specification

$$P_{s,r,y} = \beta_p B_{r,y} + \overline{\beta}^{s}_{FE}\overline{S} + \overline{\beta}^{r}_{FE}\overline{R} + \overline{\beta}_{FE}\overline{Y} + \epsilon_{s,r,y} \,,$$

where $B_{r,y}$ is the presence of a ban in RFMO $r$ in year $y$ (our treatment variable), the vectors $\{\overline{S}, \overline{R}, \overline{Y}\}$ contain fixed effect dummies for the functional group, RFMO and year respectively, and $\varepsilon_{s,r,y}$ is the error term. Note that different RFMOs implemented bans in different years, and this is captured in $B_{r,y}$. The coefficient of interest is $\beta_p$, which represents the effect of a transshipment ban on landing prices. Specifically, if $\beta_p$ is positive, this would suggest that transshipment bans increased catch prices. The results are shown in Table 7.

Outcome: Landing Prices of Fish Catch

| **Variable** | **Estimate** | **Std Error** |
|---|---|---|
| (Intercept) | $5,040^{**}$ | 532 |
| Ban Implementation | $161^{**}$ | 59 |
| Fixed effects for functional group, RFMO, year: Yes | | |

$^{*}p < 0.05$, $^{**}p < 0.01$

**Table 7 Difference-in-differences regression results and cluster-robust standard errors for yearly fish catch landing prices under the treatment of transshipment ban implementation.**

We find that the implementation of a transshipment ban increases the landing price of catch by \$161 per ton, which is a 3.2% price increase compared to the intercept of \$5,040 per ton. These results match the trends we observed in Fig. 6, where prices across RFMOs moved together prior to the implementation of bans, but split apart based on ban status after implementation.

## 5. Discussion & Concluding Remarks

Our results appear surprising for two reasons.

First, as discussed earlier, the widely-held belief among policy-makers, seafood buyers, academics, and the media is that transshipment bans are ineffective due to limited monitoring and enforcement at sea and at ports (Cullis-Suzuki and Pauly 2010, Zimmer 2017, Gianni and Simpson 2009). The game-theoretic literature would suggest that, given the limited monitoring and enforcement capabilities in this setting, a transshipment ban would indeed be ineffective, since vessels can simply ignore the ban (with low probability of getting caught) or strategically evade detection (by going dark, bribing observers, or flying flags of convenience). This belief was reflected in our conversations with key stakeholders, including procurement managers of seafood buyers, marine policy academics, and investigative journalists. Yet, despite the significant challenges in monitoring and enforcement, we find that a geographic transshipment ban is effective at reducing transshipment rates, and that strategic and evasive vessel behavior in response to the transshipment ban is minimal.

Second, economic and ecological pressures have caused fishing vessels to adopt "distant-water" fishing models that rely on the use of transshipments for bringing frozen catch back to port and resupplying fishing vessels (Pauly et al. 2003, Gianni and Simpson 2009, Tickler et al. 2018b, Mongabay 2018, Swartz et al. 2010). Thus, one may fear that the cost of reducing transshipments for vessel owners may be prohibitively high. We find that the ban only modestly increases the landing prices of catch, despite the significant decrease in transshipment rates and a change in the fishing business model. It is beyond the scope of this paper, however, to determine whether the price increase is sufficient to absorb changes in costs for vessel operators, or whether the difference in costs might be absorbed by further human exploitation.

We next discuss potential mechanisms underlying our results, and limitations of our analysis.

### 5.1. Why does the policy work?

One hypothesis is that the transshipment ban may provide a simple, clear guideline that delineates good and bad behavior for vessel owners. Legal ambiguities, coupled with poor education, can confuse supply chain actors about what constitutes problematic behavior, and lack of knowledge drives them to adopt "convenient" interpretations of the law in practice. In a study of initiatives to improve working conditions in Indonesian garment factories, Amengual and Chirot (2016) discuss how interventions can play an important role by *"diffus[ing] information about legal processes so that factory managers and unions have knowledge about the formal rules of the game... reducing information costs for factories sorting out complex and shifting policies, especially when local officials are unreliable... [these] mechanisms correspond to instances of unresolved ambiguities in rules, due either to actors' self-servingly amplifying conflicting interpretations to advance their interests or to genuine legal fuzziness."* Similarly, fishing on the high seas is subject to a complex and dynamic set of regulations, especially because no single country has jurisdiction on these waters and there are multiple stakeholders involved. The simplicity and clarity of the transshipment ban may have aided vessel owners in distinguishing and avoiding the behavior.

Second, the fact that few vessels have been caught and penalized for transshipping is frequently used as evidence for a ban's failure. For example, Zimmer (2017) criticizes the effectiveness of one regulation that proposes to blacklist fishing vessels that transship, arguing that very few vessels have been blacklisted despite significant transshipping rates (WCPFC 2018). However, the game-theoretic literature (see, *e.g.*, Dionne et al. 2009) shows that regulations can act as a deterrent to bad behavior, thereby reducing the probability of catching bad behavior. This may not mean that the policy is ineffective. In fact, we find that despite increasing incidences of transshipments worldwide, there is a significant reduction of transshipments in regions with a transshipment ban.

Third, it may be the case that the marginal cost of transshipping is in fact low. Dizon-Ross et al. (2017) study subsidy programs for bed nets in sub-Saharan Africa, where there is widespread concern that poor governance (limited health worker accountability) may undermine the effectiveness of such programs. In particular, there were concerns that workers may attempt to extort additional payments, leak subsidies to ineligible participants, or shirk their responsibilities of distribution. Yet, Dizon-Ross et al. (2017) empirically find that these policies are indeed effective, and that the majority of subsidies are distributed as intended despite ex-ante expectations that health workers may perform poorly under limited monitoring and enforcement. The authors argue that small frictions can significantly decrease corruption when marginal costs are low. In the case of bed nets, there were low gains to financial corruption and low health worker effort required to abide by the rules. Similarly, it could be the case that given the already-high rates of transshipments, cutting down on marginal transshipments may have low cost, explaining our finding that the ban significantly reduced transshipments while only slightly increasing fish catch prices. Eliminating transshipments entirely may be more costly, and would require further study.

Finally, although we have discussed our results with a wide range of industry experts, there may be mechanisms that we as a community are unaware of, and have not modeled here. This brings us to our discussion in the next subsection about the limitations of our study.

### 5.2. Limitations

First, our study is motivated by the key assumption that transshipments on the high seas are a useful surrogate for environmental and social harm. Many stakeholders — civil society groups, several UN organizations, NGOs, and marine policy academics — have namely argued that transshipments on the high seas make it easier for harm in seafood supply chains to exist and persist (Greenpeace 2016, EJF 2014, UN FAO 2001, UN ODC 2011, Ewell et al. 2017, Gianni and Simpson 2009, Urbina 2015), motivating regulatory organizations as well as seafood buyers to consider adopting a moratorium on transshipments. However, while we find that transshipment bans successfully reduce the incidence of transshipments, it is much more difficult to directly measure the resulting implications for forced labor aboard vessels. As mentioned above, we cannot rule out the case that the large reduction in transshipments in regions with a ban and the modest increase in landing prices has come at the cost of additional human exploitation. This, we believe, should be the priority of further research.

Second, transshipment bans typically only apply to a subset of fishing vessels (see Table 8 in the Appendix). Due to the small number of existing bans, we are unable to paint a picture of which types of vessels should be banned from transshipping to effectively combat harm, but this is likely an important factor to consider. For instance, in a structured survey with 260 Burmese and

Cambodian fishermen on 434 fishing jobs they had held between 2011-2016, the Issara Institute found that trafficking was over 11 times more likely to have occurred on trawlers, as compared with purse seines or other fishing vessels (Issara Institute 2017). One hypothesized driver of this difference is that purse seines have shorter trips with higher quality catch than trawlers, so they are less likely to transship catch or crew. We note that four out of the six transshipment bans in our data apply to trawlers.

Finally, while we focused on two strategic responses by vessel operators (going dark and geographical evasion), vessel owners may evade a transshipment ban in ways that we are unaware of, or lack the data to study. For instance, we are only able to detect transshipments between a fishing vessel and a larger vessel (*e.g.*, reefers, purse seines, trawlers), since only large vessels (weighing 300 tonnes or more) are mandated to be equipped with AIS transponders. One possibility is that, in response to the transshipment ban and increased awareness of scrutiny, fishing vessels have started transshipping to other (small) fishing vessels instead of reefers, thereby avoiding detection through AIS tracking. We believe that this approach is unlikely to occur because it would significantly reduce economies of scale gained through reefers and we would expect to have seen a stronger signal in AIS gaps.

## Acknowledgments

The authors gratefully acknowledge Nate Miller and David Kroodsma from Global Fishing Watch, and Jim Leape from Stanford Center for Ocean Solutions for providing us with data and invaluable assistance.

## References

ABC. 2017. Png fishing observer's disappearance raises serious safety concerns for officers at sea. Online. URL `http://www.abc.net.au/radio-australia/programs/pacificbeat/png-fishing-observers-disappearance-raises-serious/8680356`. [Last accessed October 14, 2018].

Agnew, D.J., J. Pearce, G. Pramod, T. Peatman, R. Watson, J.R. Beddington, T.J. Pitcher. 2009. Estimating the worldwide extent of illegal fishing. *PLOS One* .

Amengual, Matthew, Laura Chirot. 2016. Reinforcing the state: Transnational and state labor regulation in indonesia. *ILR Review* **69**(5) 1056–1080.

Bellman, C., A. Tipping, U.R. Sumaila. 2016. Global trade in fish and fishery products: an overview. *Marine Policy* **69** 181–188.

Boudreau, L. 2018. Multinational enforcement of labor law: Experimental evidence from bangladesh's apparel sector. *Working paper* .

Burbano, Vanessa C. 2016. Social responsibility messages and worker wage requirements: Field experimental evidence from online labor marketplaces. *Organization Science* **27**(4) 1010–1028.

Cabral, R.B., J. Mayorga, M. Clemence, S. Lynham, J.and Koeshendrajana, U. Muawanah, D. Nugroho, Z. Anna, Mira, A. Ghofar, N. Zulbainarni, S.D. Gaines, C. Costello. 2018. Rapid and lasting gains from solving illegal fishing. *Nature Ecology & Evolution* **2** 650–658.

Caro, F., L. Lane, A. Saez De Tejada Cuenca. 2018. Can brands claim ignorance? unauthorized subcontracting in apparel supply chains. *Under review* .

Chen, L., H.L. Lee. 2017. Sourcing under supplier responsibility risk: the effects of certification, audit, and contingency payment. *Management Science* **63**(9) 2795–2812.

Cullis-Suzuki, Sarika, Daniel Pauly. 2010. Failing the high seas: a global evaluation of regional fisheries management organizations. *Marine Policy* **34**(5) 1036–1042.

Daniel, P., D. Zeller. 2015. Sea around us concepts, design and data URL `www.seaaroundus.org`.

Dionne, Georges, Florence Giuliano, Pierre Picard. 2009. Optimal auditing with scoring: Theory and application to insurance fraud. *Management Science* **55**(1) 58–70.

Distelhorst, Greg, Richard M Locke, Timea Pal, Hiram Samel. 2015. Production goes global, compliance stays local: Private regulation in the global electronics industry. *Regulation & Governance* **9**(3) 224–242.

Dizon-Ross, Rebecca, Pascaline Dupas, Jonathan Robinson. 2017. Governance and the effectiveness of public health subsidies: Evidence from ghana, kenya and uganda. *Journal of public economics* **156** 150–169.

Dragusanu, Raluca, Daniele Giovannucci, Nathan Nunn. 2014. The economics of fair trade. *Journal of economic perspectives* **28**(3) 217–36.

Dunn, Daniel C, Caroline Jablonicky, Guillermo O Crespo, Douglas J McCauley, David A Kroodsma, Kristina Boerder, Kristina M Gjerde, Patrick N Halpin. 2018. Empowering high seas governance with satellite vessel tracking data. *Fish and Fisheries* .

Dyck, Alexander, Karl V Lins, Lukas Roth, Hannes F Wagner. 2018. Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics* .

EJF. 2014. Transshipment at sea, the need for a ban in west africa. Online. URL `https://ejfoundation.org/resources/downloads/ejf_transhipments_at_sea_web_0.pdf`.

Elvidge, C.D., M. Zhizhin, K. Baugh, F.-C. Hsu. 2015. Automatic boat identification system for viirs low light imaging data. *Remote Sensing* **7** 3020–3036.

Ewell, C., S. Cullis-Suzuki, M. Ediger, J. Hocevar, D. Miller, J. Jacquet. 2017. Potential ecological and social benefits of a moratorium on transshipment on the high seas. *Marine Policy* **81** 293–300.

Flaim, A., G. Subramaniam, L.M. Rendee Taylor. 2018. Eliminating human trafficking from the thai fishing industry: Perspectives of thai commercial fishing vessel owners. Bangkok: Issara Institute. URL `https://docs.wixstatic.com/ugd/5bf36e_7a763895d9734ca49febd536ab2365c6.pdf`. Last accessed August 26, 2018.

GFW. 2018. Global fishing watch faq. Online. URL `http://globalfishingwatch.org/faq/`. [Last accessed October 14, 2018].

Gianni, M., W. Simpson. 2009. The changing nature of high seas fishing: how flags of convenience provide cover for illegal, unreported and unregulated fishing. Australian Department of Agriculture, Fisheries and Forestry, International Transport Workers' Federation, and WWF International, Canberra, 2005.

Greenpeace. 2016. Turn the tide: human rights abuses and illegal fishing in thailand's overseas fishing industry. Online. URL https://www.greenpeace.org/new-zealand/publication/turn-the-tide-human-rights-abuses-and-illegal-fishing-in-thailands-overseas-fishing-industry/.

Hainmueller, Jens, Michael J Hiscox, Sandra Sequeira. 2015. Consumer demand for fair trade: Evidence from a multistore field experiment. *Review of Economics and Statistics* **97**(2) 242–256.

Harrison, Ann, Jason Scorse. 2010. Multinationals and anti-sweatshop activism. *American Economic Review* **100**(1) 247–73.

Issara Institute. 2017. Not in the same boat. Online. URL https://docs.wixstatic.com/ugd/5bf36e_9ec3ea47011343158f7c76fc7f14591f.pdf. [Last accessed October 5, 2018].

Kelleher, K., R. Willmann, R. Arnason. 2009. The sunken billions: The economic justification for fisheries reform. The World Bank.

Kraft, T., L. Valdes, Y. Zheng. 2018. Supply chain visibility and social responsibility: investigating consumers' behaviors and motives. *Manufacturing & Services Operations Management* **20**(4).

Kroodsma, D., N.A. Miller, A. Roan. 2017. The global view of transshipment: Revised preliminary findings. Online.

Kroodsma, D.A., J. Mayorga, T. Hochberg, N.A. Miller, K. Boerder, F. Ferretti, A. Wilson, B. Bergman, T.D. White, B.A. Block, P. Woods, B. Sullivan, C. Costello, B. Worm. 2018. Tracking the global footprint of fisheries. *Science* **359** 904–908.

Lam, V.W.Y., U.R. Sumaila, A. Dyck, D. Pauly, R. Watson. 2011. Construction and first applications of a global cost of fishing database. *ICES Journal of Marine Science* **68**(1996-2004).

Locke, R., M. Amengual, A. Mangla. 2009. Virtue or necessity? compliance, commitment, and the improvement of labor conditions in global supply chains. *Politics & Society* **37**(3) 319–351.

Marine Regions. 2018. Shapefiles maritime boundaries v10 world eez-v10 (2018-02-21). Online. URL http://www.marineregions.org/downloads.php. [Last accessed September 4, 2018].

McDermott, G.R., K.C. Meng, G.G. Mcdonald, C.J. Costello. 2018. The blue paradox: preemptive overfishing in marine reserves. *PNAS Latest articles* .

McDowell, R., M. Mason, M. Mendoza. 2015. Ap investigation: Slaves may have caught the fish you bought. Online. URL https://www.ap.org/explore/seafood-from-slaves/ap-investigation-slaves-may-have-caught-thefish-you-bought.html. Last accessed August 13, 2018.

Miller, D.D., U.R. Sumaila. 2014. Flag use behavior and iuu activity within the international fishing fleet: refining definitions and identifying areas of concern. *Marine Policy* **44** 204–211.

Miller, N.A., A. Roan, T. Hochberg, J. Amos, D.A. Kroodsma. 2018. Identifying global patterns of transshipment behavior. *Frontiers in Marine Science* **5**(240).

Mongabay. 2018. Industrial fishing fleets traveling farther to reel in fewer fish. Online. URL `https://news.mongabay.com/2018/08/industrial-fishing-fleets-traveling-farther-to-reel-in-fewer-fish/`.

Nakamura, K., L. Bishop, T. Ward, G. Pramod, D. Chakra Thomson, P. Tungpuchayakul, S. Srakaew. 2018. Seeing slavery in seafood supply chains. *Science Advances* **4**.

Nestle. 2017. Mars, nestle commit to clean up pet food supply chains, increasing pressure on thai union to act. Online. URL `https://www.greenpeace.org/international/press-release/7106/mars-nestle-commit-to-clean-up-pet-food-supply-chains-increasing-pressure-on-thai-union-to-act/`.

O'Leary, B.C., R.L. Brown, D.E. Johnson, H. von Nordheim, J. Ardron, T. Packeiser, C.M. Roberts. 2012. The first network of marine protected areas (mpas) in the high seas: the process, the challenges and where next. *Marine Policy* **36**(3) 598–605.

Pauly, Daniel, Jackie Alder, Elena Bennett, Villy Christensen, Peter Tyedmers, Reg Watson. 2003. The future for fisheries. *Science* **302**(5649) 1359–1361.

Pintassilgo, P., M. Finus, M. Lindroos, G. Munro. 2010. Stability and success of regional fisheries management organizations. *Environmental and Resource Economics* **46**(3) 377–402.

Plambeck, Erica L, Terry A Taylor. 2015. Supplier evasion of a buyer's audit: Implications for motivating supplier social and environmental responsibility. *Manufacturing & Service Operations Management* **18**(2) 184–197.

Pramod, G., K. Nakamura, T.J. Pitcher, L. Delagran. 2014. Estimates of illegal and unreported fish in seafood imports to the usa. *Marine Policy* **48** 102–113.

Pramod, G., T.J. Pitcher, G. Mantha. 2017. Estimates of illegal and unreported seafood imports to japan. *Marine Policy* **84** 42–51.

Robards, MD, GK Silber, JD Adams, J Arroyo, D Lorenzini, K Schwehr, J Amos. 2016. Conservation science and policy applications of the marine vessel automatic identification system (ais)—a review. *Bulletin of Marine Science* **92**(1) 75–103.

Short, Jodi L, Michael W Toffel, Andrea R Hugill. 2016. Monitoring global supply chains. *Strategic Management Journal* **37**(9) 1878–1897.

Swartz, W., E. Sala, R. Watson, D. Pauly. 2010. The spatial expansion and ecological footprint of fisheries (1950 to present). *PLoS ONE* **5**(12).

Teh, L.C.L., U.R. Sumaila. 2013. Contribution of marine fisheries to worldwide employment. *Fish and fisheries* (14) 77–88.

Thai Union Group. 2017. Greenpeace and thai union group—summary of agreement. Online. URL https://www.greenpeace.org/archive-international/Global/international/documents/oceans/Thai-Union-Commitments.pdf.

The Guardian. 2017. Nine of the world's biggest fishing firms sign up to protect oceans. Online. URL https://www.theguardian.com/environment/2017/jun/09/nine-of-worlds-biggest-fishing-firms-sign-up-to-protect-oceans.

Tickler, D., J.J. Meeuwig, K. Bryant, F. David, J.A. Forrest, E. Gordon, J.J. Larsen, B. Oh, D. Pauly, U.R. Sumaila, D. Zeller. 2018a. Modern slavery and the race to fish. *Nature Communications* **9**(4643).

Tickler, D., J.J. Meeuwig, M.-L. Palomares, D. Pauly, D. Zeller. 2018b. Far from home: distance patterns of global fishing fleets. *Science Advances* **4**.

Toffel, Michael W, Jodi L Short, Melissa Ouellet. 2015. Codes in context: How states, markets, and civil society shape adherence to global labor standards. *Regulation & Governance* **9**(3) 205–223.

UN FAO. 2001. International plan of action to prevent, deter, and eliminate illegal, unreported and unregulated fishing. Online. URL http://www.fao.org/3/a-y1224e.pdf.

UN FAO. 2011. Fao technical guidelines for responsible fisheries, no. 1. Online. URL http://www.fao.org/tempref/docrep/fao/003/W3591e/W3591e00.pdf.

UN FAO. 2016. State of the world's fisheries and aquaculture. Online. URL www.fao.org/3/a-i5555e.pdf.

UN FAO. 2018. Regional fishery bodies map viewer. Online. URL http://www.fao.org/figis/geoserver/factsheets/rfbs.html. Last accessed August 28, 2018.

UN ODC. 2011. Transnational organized crime in the fishing industry. Online. URL http://www.unodc.org/documents/human-trafficking/Issue_Paper_-_TOC_in_the_Fishing_Industry.pdf.

Urbina, I. 2015. 'sea slaves:' the human misery that feeds pets and livestock. New York Times. URL https://www.nytimes.com/2015/07/27/world/outlaw-ocean-thailand-fishing-sea-slaves-pets.html. Last accessed November 20, 2018.

US DOL. 2016. List of goods produced by child labor or forced labor. Online. URL https://www.dol.gov/sites/default/files/documents/ilab/reports/child-labor/findings/TVPRA_Report2016.pdf.

WCPFC. 2016. 8th annual report for the regional observer programme. Online. URL https://www.wcpfc.int/system/files/WCPFC-TCC12-2016-RP02\%20Rev\%202\%208th\%20Annual\%20ROP\%20Report\%20TCC12.pdf. [Last accessed October 14, 2018].

WCPFC. 2018. Wcpfc record of fishing vessels. Online. URL https://www.wcpfc.int/record-fishing-vessel-database?flag=All&field_vessel_submitted_by_ccm_value=All&type=Longliner&name=&ircs=&win=&vid=&imo=&auth_tranship_hs=Yes&fishing_methods=All. Last accessed August 13, 2018.

Windward. 2014. Ais data on the high seas: An analysis of the magnitude and implications of growing data manipulation at sea. Online. URL https://www.arbitrage-maritime.org/fr/Gazette/G36complement/Windward.pdf.

Zimmer, K. 2017. How seafood's "dark web" obscures fraud, fish laundering, and slavery on the high seas. Online. URL http://www.iuuwatch.eu/2017/08/seafoods-dark-web-obscures-fraud-fish-laundering-slavery-high-seas/.

# Appendix

Transshipment bans in most RFMOs only prohibited transshipments for certain types of fishing vessels. Table 8 below shows the specific vessel types targeted by transshipment bans in each RFMO.

| RFMO | Banned vessels |
|---|---|
| SEAFO | All vessels |
| IATTC | All purse seine vessels & small longline vessels |
| ICCAT | All vessels except large-scale pelagic long-line vessels |
| IOTC | All vessels except large-scale pelagic long-line vessels |
| GFCM | All vessels except large-scale pelagic long-line vessels & all transshipments at sea of bluefin tuna |
| WCPFC | All purse seine vessels. |

**Table 8  Summary of vessel types targeted by different transshipment bans.**

Fig. 9 shows a histogram of the duration of loitering events. 99% of loitering events last for 4.75 hours or greater, and the median duration was 7.5 hours.

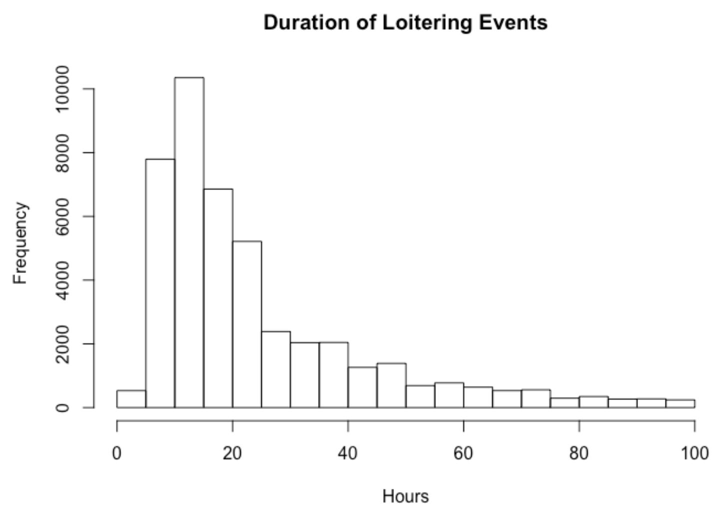


**Figure 9  Histogram of duration of loitering events compiled by GFW.**

Fig 10 shows AIS coverage gaps that lasted greater than 7.5 hours (the median length of loitering events) on the high seas over time in regions with and without a transshipment ban. We note that the results are qualitatively similar to Fig 4.

Table 9 shows regression results for the yearly change in AIS gaps (that are at least 7.5 hours long) as a function of transshipment ban status. The results are very similar to Table 5.

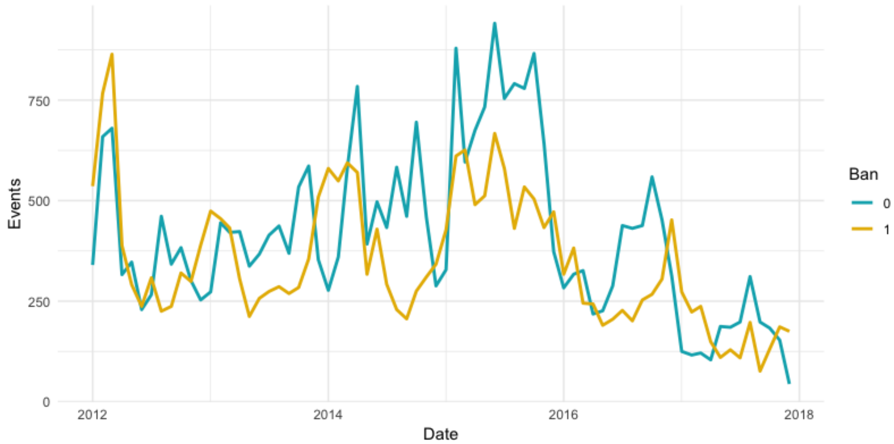


**Figure 10** **Events where a vessel's AIS signal went dark over 7.5 hours in RFMOs over time in regions where a transshipment ban is in effect (yellow) and where no ban is in effect (blue).**

Outcome: Yearly Change in AIS Gap Rate

| **Variable** | **(1) Location at Start of Gap** | | **(2) Location at End of Gap** | |
|---|---|---|---|---|
| | **Estimate** | **Std Error** | **Estimate** | **Std Error** |
| (Intercept) | 0.56** | 0.19 | 0.56** | 0.15 |
| Is 2014 | 0.08 | 0.06 | 0.06 | 0.09 |
| Is 2015 | 0.10 | 0.11 | 0.11 | 0.08 |
| Is 2016 | −0.29** | 0.11 | −0.29** | 0.09 |
| Is 2017 | −0.21 | 0.18 | −0.21 | 0.12 |
| **Ban** | **−0.31*** | **0.14** | **−0.31*** | **0.12** |

*$p < 0.05$, **$p < 0.01$

**Table 9** **Regression results with cluster-robust standard errors for yearly change in AIS gap rates per starting grid cell (left) or ending grid cell (right) as a function of transshipment ban status.**