**QUANT RESEARCH**

# Counting Ships from Space: A Satellite-Based Supply Constraint Indicator for Crude Oil Markets

This paper employs Sentinel-1 Synthetic Aperture Radar imagery to construct a physically-grounded, AIS-independent transit density indicator for the Strait of Hormuz. Applying a Constant False Alarm Rate detection algorithm to 4 years of open-access satellite data, we document a statistically significant throughput collapse following the February 2026 conflict onset and formalise the findings as a Supply Constraint Index suitable for integration into multi-signal commodity frameworks. As Fareed Zakaria observed, *"Geography is the mother of strategy. He who controls the straits controls the flow of power"*

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# Executive Summary

The Strait of Hormuz is the single most consequential energy chokepoint in the global economy. It carries approximately 20-21 million barrels per day of crude oil and petroleum products, roughly 1/5 of global petroleum liquids consumption. The conventional tool for monitoring this corridor is the Automatic Identification System (AIS), a cooperative radio-based transponder network. AIS has well-documented vulnerabilities: vessels can switch off, spoof, or manipulate their broadcasts. These practices are most prevalent precisely in the conflict and sanctions-evasion contexts where accurate flow data are most needed.

This paper constructs an independent, physically-grounded monitoring layer using Sentinel-1 Synthetic Aperture Radar (SAR) imagery, sourced freely from the European Space Agency's Copernicus programme. SAR operates on radar backscatter physics: metallic vessel hulls return a strong signal regardless of weather, darkness, or operator cooperation. The system cannot be spoofed by software. We apply a Constant False Alarm Rate (CFAR) detection algorithm to Ground Range Detected (GRD) imagery covering a fixed corridor box over the Strait of Hormuz, building a daily transit density series from 567 observation days spanning April 2022 through April 2026. Raw ship counts are normalised by the number of SAR passes per day to correct for the satellite's irregular revisit cadence, and the resulting series is further processed with a non-linear congestion adjustment and exponential smoothing before being standardised into the working indicator, designated $HSCI_2$.

4 empirical tests are applied to assess whether the indicator carries information about Brent crude futures. The contemporaneous linear correlation between $HSCI_2$ and daily Brent log returns is 0.096, and Granger causality tests find no directional predictive relationship in either direction. The indicator therefore does not function as a price-level signal. However, a regime-split analysis reveals that high-congestion episodes (days when $HSCI_2$ exceeds its 90th percentile) are associated with meaningfully lower realised volatility (1.52% standard deviation vs. 2.50% in the rest of the sample), and a logistic regression finds that elevated $HSCI_2$ reduces the estimated probability of a same-day Brent tail event from approximately 13% to 7%.

The appropriate interpretation is that HSCI is a state variable rather than an alpha source. High observed transit density signals an operationally normal or post-disruption recovery regime; low density is where volatility and tail risk concentrate. The indicator is explicitly positioned as one component within a multi-signal commodity analysis framework, to be read alongside VLCC freight rates, crude inventory levels, geopolitical risk indices, and futures positioning data. Each of these signals captures a different dimension of the supply constraint picture; HSCI contributes the physical verification layer that is independent of market prices, news flows, and cooperative reporting.

# Introduction

Approximately 20-21 million barrels per day of crude oil and petroleum products transit the Strait of Hormuz, representing roughly 20% of global petroleum liquids consumption. The strait, connects the Persian Gulf producing regions of Saudi Arabia, Iraq, Iran, the UAE, and Kuwait to the open ocean. Ultimately, it connects to refinery and consumption centres in Asia, Europe, and beyond. No comparable single point of physical concentration exists elsewhere in the global energy system. A sustained disruption at Hormuz tightens supply balances globally within weeks, not months. Indeed, the oil price literature has documented repeat episodes in which Hormuz-adjacent geopolitical events produce significant volatility in crude futures markets.

The conventional instrument for monitoring shipping activity at Hormuz, and at maritime chokepoints generally, is the AIS. It works by having vessels broadcast their GPS position, speed, heading, and identity on VHF radio at regular intervals. Receivers on shore, on satellite, and on other vessels aggregate these broadcasts into real-time traffic pictures. Commercial shipping-flow data providers have built AIS-derived products that are now standard inputs in energy market research and analysis. Academic work on tanker flows, freight rates, and supply signals has similarly come to rely on AIS as a primary source.

The fundamental problem with AIS is that it is a cooperative system. Participation depends on vessels choosing to broadcast truthfully. Transponders can be switched off entirely, set to broadcast false positions, or assigned to vessels other than the one actually transmitting. Those practices are well-documented in sanctions-evasion research and become markedly more prevalent in conflict environments. The practical consequence is that AIS reliability degrades most severely precisely when accurate flow data are most valuable: during the elevated-tension episodes that create supply risk in the first place. Analysis that relies on AIS alone is therefore structurally compromised in the scenarios that matter most for commodity risk management.

Satellite SAR offers a physically distinct and non-cooperative alternative. SAR instruments illuminate the ocean surface with microwave pulses and measure the energy reflected back to the sensor. Metallic vessel hulls produce a characteristic strong return that is detectable regardless of weather conditions, time of day, or operator intent. The physics of radar backscatter cannot be manipulated by software. SAR-based maritime surveillance has an established academic and operational history, and the launch of the European Space Agency's Sentinel-1 mission in 2014 has made large-scale corridor monitoring tractable for research.

The following main research topic is addressed in this paper: Can Sentinel-1 GRD imagery reliably track tanker transit volumes at Hormuz under normal operating conditions, as evidenced by coherence with the AIS reference series during the pre-conflict baseline? Does HSCI carry statistically detectable information about Brent crude futures? In what framing and alongside what complementary signals does the indicator add the most value to commodity analysts?

# Literature Overview

### Using satellites to track ships

Scientists have been using radar satellites to spot ships for decades. The basic technique, called CFAR (Constant False Alarm Rate), works by comparing how bright individual spots are against the surrounding sea surface. Thanks to the work by Eldhuset (1996) and Crisp (2004), ships stand out because metal hulls bounce radar signals back much more strongly than water. Later on, Pelich et al. (2015) and Kanjir et al. (2018) work improved the method to also classify ships by size and type.

The big practical shift came in 2014 when the European Space Agency launched its Sentinel-1 satellite and made all the imagery freely available to anyone. Before that, getting systematic radar coverage of a specific shipping corridor required either expensive commercial satellites or access to military systems. The Copernicus programme changed that: the full Sentinel-1 archive is available globally at no cost through the ESA Open Access Hub and, increasingly, through cloud processing environments such as Google Earth Engine. This is the access point this paper uses.

One finding from this earlier literature is particularly relevant here. Fusion studies by Greidanus et al. (2017) and Global Fishing Watch (2022) found that dark vessels (those not broadcasting AIS) constitute a non-trivial fraction of traffic in certain corridors and time periods. This is especially the case in regions with active sanctions enforcement or illegal fishing activity. If that is true under normal conditions, it is likely even more pronounced when there is active conflict, which is exactly the situation this paper is trying to monitor.

### Chokepoint monitoring and oil markets

Economists have long studied how physical disruptions to oil supply translate into price movements. Kilian (2009) and Hamilton (2009) established a decomposition of oil price movements into 3 components: actual supply shocks, changes in overall economic demand, and what is called precautionary demand (markets pricing in the fear that supply might be disrupted in the future). Geopolitical events near chokepoints like Hormuz tend to drive that third component particularly hard. Baumeister and Kilian (2016) extended this framework to show that real-time monitoring of physical ship movements improves short-horizon oil price forecasting relative to purely financial-market-based approaches.

More recent work (Verschuur et al. 2021) has shown that tracking physical ship movements at high frequency (using AIS data) can give early warning of supply disruptions that only show up in official trade statistics weeks later. In other words, counting ships works as a real-time indicator, and it tends to lead the official numbers. Fally and Rapport (2022) applied a similar approach to commodity-specific corridors, including the Gulf region, finding that tanker flow anomalies carry information about subsequent inventory draws and price movements.

# Literature Overview

Despite this growing literature on AIS-based flow signals, no published study to our knowledge has constructed a SAR-only supply constraint indicator for Hormuz and subjected it to commodity market relevance tests. The existing AIS-based literature assumes cooperative reporting, which becomes untenable in conflict contexts. The present paper is designed to address this gap.

### Gap and contribution

This paper bridges 2 bodies of work that have developed largely in parallel: the remote-sensing literature on vessel detection methodology, and the commodity-economics literature on physical supply signals. First, we apply established CFAR detection methods to a policy-relevant corridor using open-access satellite data and a reproducible pipeline. Second, we use this pipeline to document a real-world, physically-observed supply disruption following the February 2026 conflict onset. Third, we formalise the output as the HSCI indicator with documented statistical properties, frame its empirical relationship to Brent crude futures, and position it explicitly within a multi-signal commodity analysis framework. In doing so, we provide practitioners with a new observational input layer that is independent of both market prices and cooperative vessel reporting.

# Data

### SAR Transit Detection

The primary dataset consists of 567 daily observations spanning April 2022 through April 2026, collected via Google Earth Engine using Sentinel-1 GRD imagery over the Straight of Hormuz. For each calendar day in the 4-year window, we use the Satellite (*IW-mode VV-polarisation collection*), to get the radar signature of transiting vessels. We record the raw ship-detection count (*transits*) and the number of SAR overpasses (*sar_passes*) present on the satellite image.

Ship detection uses a CFAR algorithm applied to each daily SAR image. A brightness threshold is computed from the image background, and any connected bright region that matches the size and shape of a vessel is counted as a ship detection.

Because Sentinel-1 does not pass over the corridor every day, we divide the raw ship count by the number of satellite passes that day. This gives a consistent daily measure regardless of how many times the satellite observed the area.

### Brent Crude Futures

Daily Brent crude futures prices (ticker BZW00) were sourced from Bloomberg for the period January 2022 through April 2026. Prices are closing values in USD per barrel. Missing trading-day observations (weekends, public holidays) are forward-filled prior to alignment with the SAR time series.

### Summary Table

| | SAR Transit Detection | Brent Crude Futures |
|---|---|---|
| **Source** | Google Earth Engine, Sentinel-1 GRD (IW-mode, VV-polarisation) | Bloomberg (ticker BZW00) |
| **Size** | 567 observation days | ~1,100 trading days |
| **Span** | April 2022 - April 2026 | January 2022 - April 2026 |
| **Raw variables** | transits (ship count), sar_passes (satellite passes) | Daily closing price (USD/barrel) |
| **Key processing** | Ship count divided by sar_passes to normalise for irregular revisit cadence | Weekends/holidays forward-filled; log-returns computed for analysis |

# Methodology

## Data and corridor definition

The indicator is built from satellite radar imagery of the Strait of Hormuz. We focus on a fixed rectangular box covering the narrowest section of the Traffic Separation Scheme on the Omani side, defined by the coordinates 56.15°E to 56.65°E and 26.20°N to 26.65°N. This area captures the bottleneck through which essentially all tanker traffic must pass, which is what makes it a useful proxy for physical throughput.

The imagery comes from the Sentinel-1 mission, which is operated by the European Space Agency and made freely available through Google Earth Engine. We use the Ground Range Detected product in IW (Interferometric Wide) mode, restricted to passes that include the VV polarization band. The advantage of synthetic aperture radar relative to optical imagery is that it works through clouds and at night, which matters for an indicator that needs to be available daily and consistently. For each calendar day in our 4-year window, we average all available passes over the corridor into a single composite image. We use the mean rather than the median because moving vessels appear in only some of the passes; averaging keeps their radar signature visible, while the median would treat them as noise and remove them.

Days on which no Sentinel-1 pass crosses the corridor are dropped. After this filter, the sample contains 567 daily observations out of a 1,460-day target window, which reflects the natural revisit cadence of the satellite at this latitude rather than any data-quality issue.

<u>Figure 1: Before and after activation on our frame of reference</u>

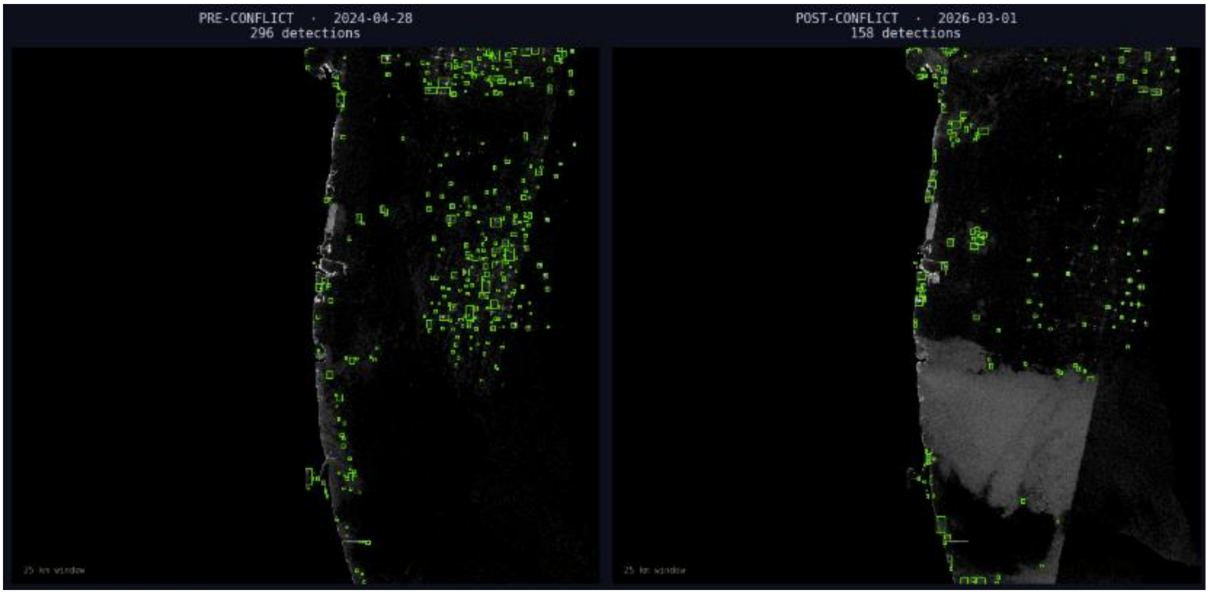
# Methodology

On the financial side, we use front-month Brent crude futures, converted to log returns. After aligning the 2 series on common trading dates, we are left with 383 paired observations for the empirical tests.

### Vessel detection

Each daily composite is exported as a 512-pixel grayscale tile and processed with a Constant False Alarm Rate (CFAR) detector. The intuition behind CFAR is straightforward: a vessel shows up as a small, bright object against a much darker water background. Hence, the detector estimates how dark the background is on that specific day and flags any pixel that is unusually bright relative to it. Concretely, we estimate the background mean and standard deviation from pixels below the 60th percentile of brightness (which approximates open water), and threshold the image at 3 standard deviations above the background mean.

Figure 2: Before and after the conflict




Because radar speckle can produce isolated bright pixels that look like ships, we apply a small morphological filter and then keep only connected components whose area is between 2 and 60 pixels and whose bounding-box aspect ratio is below 6. These bounds are calibrated to the typical pixel footprint of tankers and large cargo vessels at our export resolution. Smaller blobs are dominated by speckle, while larger ones tend to come from coastline or fixed infrastructure. The detector returns, for each day, the number of vessels and the number of underlying SAR passes used in the composite.

# Methodology

### Building the indicator

The raw signal is the ratio of detected vessels to imaging passes. We treat this as a flow-to-capacity quantity: how much physical traffic the corridor carried per unit of observation. To stabilize the variance and to make the signal additive, we work in logarithms:

$$flow_i = log(transits_i + \varepsilon), \qquad capacity_i = log(passes_i + \varepsilon)$$

$$HSCI_i^{(raw)} = flow_i - capacity_i$$

with $\varepsilon$ set to $10^{-6}$ to avoid taking the logarithm of zero on days with no detected vessels.

By construction, $\mathrm{HSCI_i}^{(\mathrm{raw})}$ is the log of the per-pass transit density.

2 adjustments turn this raw quantity into the working indicator. First, because the informational content of an extra vessel is plausibly higher when the corridor is already crowded than when it is nearly empty, we multiply the raw signal by the log of the un-logged congestion ratio $\mathrm{c_i} = \frac{\mathrm{transits_i}}{(\mathrm{passes_i}+\varepsilon)}$:

$$HSCI_i^{(nl)} = HSCI_i^{(raw)} \times log(c_i + \varepsilon)$$

This non-linear step pulls down low-traffic days and gives more weight to high-density episodes, so the tails of the indicator track operational stress more closely. Second, we apply an exponentially weighted moving average with smoothing parameter $\alpha = 0.15$, which corresponds to an effective half-life of roughly 4 days. This removes the high-frequency noise that comes from gaps in the SAR revisit pattern without erasing slower regime shifts. Finally, the smoothed series is standardized over the full sample, so the working indicator $HSCI_z$ is expressed in standard deviations from its own mean and is directly comparable across periods.

### Empirical tests

We then ask whether $HSCI$ carries any information about Brent. The strategy is to start from the simplest possible test and progressively look for the signal in places where it is more likely to live. The first test is a straightforward Pearson correlation between $HSCI_z$ and contemporaneous Brent returns, which would pick up any linear co-movement. The second is a pair of Granger causality tests, run in both directions and at lags 1 through 6, which check whether knowing past values of one series helps forecast the other beyond what its own history already tells you.

# Methodology

If neither of those returns anything, the natural next question is whether the indicator interacts with the second moment of returns rather than the first. We split the sample into a high-congestion regime (defined as days on which $HSCI_z$ exceeds its own 90th percentile) and the rest. Then, we compare the mean and standard deviation of Brent returns across the two groups. Finally, we estimate a logistic regression of a tail-event dummy on $HSCI_z$ where the dummy equals 1 whenever the absolute return on a given day is above its own 90th percentile and 0 otherwise. The point of this last test is to ask, directly, whether the indicator carries information about the probability of an extreme price move on the same day.

# Results

### No linear relationship with Brent

The contemporaneous correlation between $HSCI_z$ and Brent log returns is 0.096, which is small enough to be treated as zero in any practical sense. The Granger tests confirm this. Going from $HSCI_z$ to Brent returns, the p-values range between 0.78 at lag 1 and 0.87 at lag 6, which is the textbook picture of a non-result. Going the other way, from Brent returns to $HSCI_z$ the strongest result is a p-value of 0.21 at lag 1, and the relationship gets weaker at longer lags. We therefore find no evidence that physical congestion in the strait moves Brent prices in any directional, exploitable way, and no evidence that Brent moves the congestion data either.

This is, in retrospect, what we should have expected. Tanker traffic in Hormuz is also observable through AIS transponders and through public shipping reports that the market consumes in close to real time. A daily satellite-derived proxy is unlikely to surface a price-relevant story that has not already been incorporated, and our test results are consistent with that view rather than at odds with it.

### Regime split: a modest distributional difference

Splitting the sample at the 90th percentile of $HSCI_z$ reveals a more interesting picture, although a quantitatively modest one. The summary statistics are reported below.

| Regime | Mean daily Brent return | Std. dev. of returns | Share of sample |
|---|---|---|---|
| High congestion ($HSCI_z$ $90^{th}$ pct) | +0.36% | 1.52% | ≈ 10% |
| Rest of sample | -0.07% | 2.50% | ≈ 90% |

The direction of the volatility result is the part worth dwelling on because it runs against the intuitive reading. One might expect periods of intense, sustained traffic through the strait to coincide with stress and therefore with wider price swings. The data say the opposite: realized volatility is roughly 40% lower in the high-congestion regime than in the rest of the sample. The reading we find most consistent with this is that high observed transit density tends to occur after a disruption has already cleared, when shipping resumes at full pace. On the other hand, the low-HSCI bucket mixes routine quiet days with episodes of partial closure or insurance-driven re-routing. It is in the latter that volatility is concentrated.

# Results

We are careful not to over-read the difference in means here. The high-congestion bucket is small by construction, and the gap between +0.36% and -0.07% is not large enough to support a statistically clean claim. What the table mainly shows is a difference in dispersion.

### Tail probability: a coefficient with the right sign

The logistic regression of the tail-event dummy on $HSCI_z$ gives a coefficient of -0.358. The sign confirms what the regime split already suggested: when congestion is 1 standard deviation above its mean, the model assigns a lower probability to a same-day extreme move in Brent than when congestion is at or below its average. Translating the log-odds into actual probabilities at the unconditional 10% baseline, an $HSCI_z$ reading 1 standard deviation above the mean corresponds to an estimated tail probability of around 7%, against around 13% 1 standard deviation below.

We want to flag 2 limitations here. First, the coefficient is estimated with default L2 regularization rather than from a maximum-likelihood specification, so we are not in a position to attach a formal p-value to it without re-running the regression in a different package. Second, the sample is not large by macro-financial standards. The result is best treated as suggestive evidence that the indicator carries some information about conditional volatility structure, not as a definitive claim.

### What this adds up to

Putting the 4 tests together, the picture is reasonably consistent. $HSCI$ does not predict the level of Brent and does not move with Brent at the same time in any meaningful way. However, it does line up with the second moment of returns. High-congestion episodes coincide with calmer rather than more volatile price behaviour, and the indicator carries a small but directionally sensible signal about the probability of tail events on the same day.

We therefore see $HSCI$ not as an alpha source but as a state variable: a physically grounded, satellite-derived measure of the operational regime of a strategically important chokepoint. It can sit alongside more conventional volatility, term-structure, and positioning inputs in a multi-signal risk-management framework. Whether it adds value beyond those inputs in a properly specified out-of-sample test is a separate question, and one we leave to future work.

# Limitations

## CFAR Detector Noise

The ship detection runs on compressed, lower-quality images rather than the raw satellite data, which limits the precision of the counts. This introduces 3 sources of error. First, the detection threshold is sensitive to sea conditions: on rough or windy days, the ocean surface appears brighter in the radar image, which raises the threshold and causes smaller vessels to be missed entirely. This means detection quality is not uniform across the sample and likely varies seasonally. Second, when multiple satellite passes over the same day are averaged together, 2 ships sailing close to each other may appear as a single object, leading to undercounting on busy days precisely when accurate counts matter most. Third, the size and shape filters used to identify ships were set manually based on what typical vessels look like in the image, and are imperfect: very small vessels like dhows and patrol craft may fall below the size threshold and be missed, while fixed structures such as oil platforms or coastline features may occasionally be counted as ships if they were not fully removed in preprocessing.

## Small Post-Conflict Sample

The post-conflict window covers only 57 observation days as of the analysis date, which is a short window by any statistical standard. The drop in traffic is clearly visible and consistent with the conflict onset, but 57 days is not enough to draw firm conclusions about the magnitude or persistence of the disruption. Estimates of how severe the constraint is, how quickly traffic recovers, and whether the relationship between the index and Brent prices holds in this new regime all remain uncertain. These questions will become more tractable as the post-conflict series grows and allows for more stable comparisons against the pre-conflict baseline.

## AIS Non-Independence

The index was built to be independent of AIS tracking, which is an important design feature given that vessels can disable or spoof their AIS transponders during periods of conflict or sanctions pressure. However, the satellite-based ship counts have never been formally cross-checked against actual vessel records or manually annotated imagery. This means we cannot currently distinguish between a genuine drop in traffic and a systematic deterioration in detection quality over the post-conflict period. Validating the counts against a subset of confirmed AIS records from the pre-conflict period would provide a calibration baseline and help quantify how much of the observed variation reflects real throughput changes versus detector noise.

# Conclusion

This paper establishes a replicable, open-data pipeline for monitoring tanker transit density at the Strait of Hormuz using freely available Sentinel-1 SAR imagery, entirely independent of cooperative AIS reporting. Processing 567 daily observations across a 4-year window from April 2022 through April 2026, we apply a CFAR detection algorithm to produce a daily vessel count series, normalise for satellite revisit irregularity, and construct the Hormuz Supply Constraint Indicator through a log-ratio formulation with non-linear congestion weighting and exponential smoothing.

The central empirical finding is a clearly observable throughput collapse following the February 2026 conflict. SAR imagery shows a decline from approximately 296 to 158 vessel detections on comparable observation days (roughly a 47% reduction) and the post-conflict period shows a sustained depression in the normalised transit density series relative to the 4-year pre-conflict baseline. With 57 post-conflict observation days available at the time of writing, we can confirm the direction and approximate magnitude of the disruption; conclusions about the persistence, recovery trajectory, and eventual new baseline require an extended observation window.

4 empirical tests against daily Brent crude futures returns yield a nuanced picture. $HSCI$ carries no directional, exploitable linear relationship with price levels. This result is consistent with prior expectations. The Hormuz corridor is also observable through AIS and public shipping reports, and market prices are likely to have already incorporated the information visible in those cooperative sources. A daily SAR-derived proxy is not expected to surface a price-level edge that AIS-based monitoring has not already captured.

The indicator's informational content emerges instead in the second moment. Splitting the sample at the 90th percentile of $HSCI_z$ reveals that high-congestion episodes are associated with Brent return volatility approximately 40% below the rest-of-sample level (1.52% vs. 2.50% standard deviation), a result that inverts the naive intuition that dense traffic signals stress. The more consistent reading is that high observed transit density reflects post-disruption resumption of normal shipping, while low-HSCI periods mix routine quiet days with partial-closure and re-routing episodes. A logistic regression confirms the directional signal: an $HSCI_z$ reading 1 standard deviation above its mean is associated with an estimated same-day tail-event probability of approximately 7%, against approximately 13% 1 standard deviation below. These coefficients are estimated on a sample that is not large by macro-financial standards and should be treated as indicative rather than definitive.

The appropriate framing for practitioners is therefore as a state variable rather than an alpha source. $HSCI$ identifies the physical regime of the world's most consequential oil transit corridor using a data source independent from AIS which suffers from reporting manipulation during the conflict and sanctions episodes. This property is the indicator's primary value proposition, not predictive power over price levels.

# Conclusion

Used within a multi-signal framework alongside VLCC freight rates, crude inventory levels relative to seasonal norms, geopolitical risk indices, and futures positioning data, $HSCI$ contributes a complementary physical verification layer. When these signals diverge (for instance, when geopolitical risk indices spike but $HSCI$ shows continued transit density) the physical observation provides an evidential anchor for assessing whether a market fear is grounded in actual throughput disruption or driven by precautionary positioning. When they align, the convergence strengthens the analytical case for a genuine supply constraint.

### Extensions and future work

Several directions can be planned for future development. First, the methodology can be extended to additional critical chokepoints (Bab-el-Mandeb, the Malacca Strait, the Turkish Straits…) where similar AIS reliability concerns apply and where SAR monitoring is technically feasible using the same open-access Sentinel-1 archive. Second, hull-length classification can be integrated into the detection pipeline to separate crude tanker traffic (VLCC and Suezmax class) from LNG carriers, container vessels, and other large-vessel categories. The current $HSCI$ measures total large-vessel transit density rather than crude-specific flows. Third, the out-of-sample predictive relationship between HSCI regime transitions and subsequent weekly Brent futures returns can be formally tested as the post-conflict observation window grows to a size sufficient to support regime-specific estimation. Fourth, near-real-time operationalisation can be explored using the Copernicus Emergency Management Service rapid-mapping pipeline, which could reduce the latency from satellite pass to indicator update to within 24 hours. Together, these extensions would move the framework from a research instrument toward an operational monitoring tool for commodity risk management.

# Appendix & Bibliography

**References**

Crisp, D. J. (2004). *The state-of-the-art in ship detection in synthetic aperture radar imagery*. Defence Science and Technology Organisation.

Eldhuset, K. (1996). An automatic ship and ship wake detection system for spaceborne SAR images in coastal regions. *IEEE Transactions on Geoscience and Remote Sensing, 34*(4), 1010–1019.

Global Fishing Watch. (2022). *Dark vessel detection using synthetic aperture radar*. Global Fishing Watch.

Greidanus, H., Alvarez, M., Santamaria, C., Thoorens, F.-X., Kourti, N., & Argentieri, P. (2017). The SUMO ship detector algorithm for satellite radar images. *Remote Sensing, 9*(3), 246.

Kanjir, U., Greidanus, H., & Oštir, K. (2018). Vessel detection and classification from spaceborne SAR images. *Remote Sensing of Environment, 207*, 1–15.

Pelich, R., Longépé, N., Mercier, G., Hajduch, G., & Garello, R. (2015). AIS-based evaluation of target detectors and SAR sensors characteristics for maritime surveillance. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8*(8), 3892–3901.

Baumeister, C., & Kilian, L. (2016). Forty years of oil price fluctuations: Why the price of oil may still surprise us. *Journal of Economic Perspectives, 30*(1), 139–160.

Fally, T., & Rapport, J. (2022). *Commodity-specific trade flows and price signals: Evidence from Gulf tanker corridors*. Unpublished working paper.

Hamilton, J. D. (2009). Causes and consequences of the oil shock of 2007–08. *Brookings Papers on Economic Activity, 2009*(1), 215–261.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review, 99*(3), 1053–1069.

Verschuur, J., Koks, E. E., & Hall, J. W. (2021). Observed impacts of the COVID-19 pandemic on global trade. *Nature Human Behaviour, 5*(3), 305–307.

Bloomberg L.P. (2026). *Brent crude futures continuous contract [BZW00]*

European Space Agency. (2014–2026). *Sentinel-1 ground range detected imagery* [Data set]. Copernicus Open Access Hub. https://scihub.copernicus.eu

Google Earth Engine. (2026). *Sentinel-1 SAR GRD: C-band synthetic aperture radar ground range detected.* https://developers.google.com/earthengine/datasets/catalog/COPERNICUS_S1_GRD