2026-04

IUMI Hull Inflation Index

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Executive Summary

As macroeconomic pressure continues to affect global trade and repair dynamics, marine insurers seek tools to better understand the drivers behind rising hull claim costs. The IUMI Hull Inflation Index addresses this need by quantifying the relationship between three key economic variables and the evolution of average marine hull claims:

(1) the price of hot-rolled steel products as a proxy for material costs,
(2) indexed and weighted construction - sector wages in key shipbuilding regions (China, South Korea, Japan, and Europe), and
(3) global shipyard capacity as measured by the Forward Cover indicator published by Clarkson’s Research.

These factors were selected for their theoretical relevance and data availability, and entered into a Generalized Linear Model (GLM) calibrated against indexed benchmark data provided by Cefor, The Nordic Association of Marine Insurers. The benchmark data reflects the average cost of claims as incurred under Hull & Machinery coverages. Total losses are excluded as the index is meant to reflect drivers of repair cost drivers, whereas total losses reflect changes in vessel values which are subject to different factors. The model explains approximately 87% of the variance in observed claim costs.

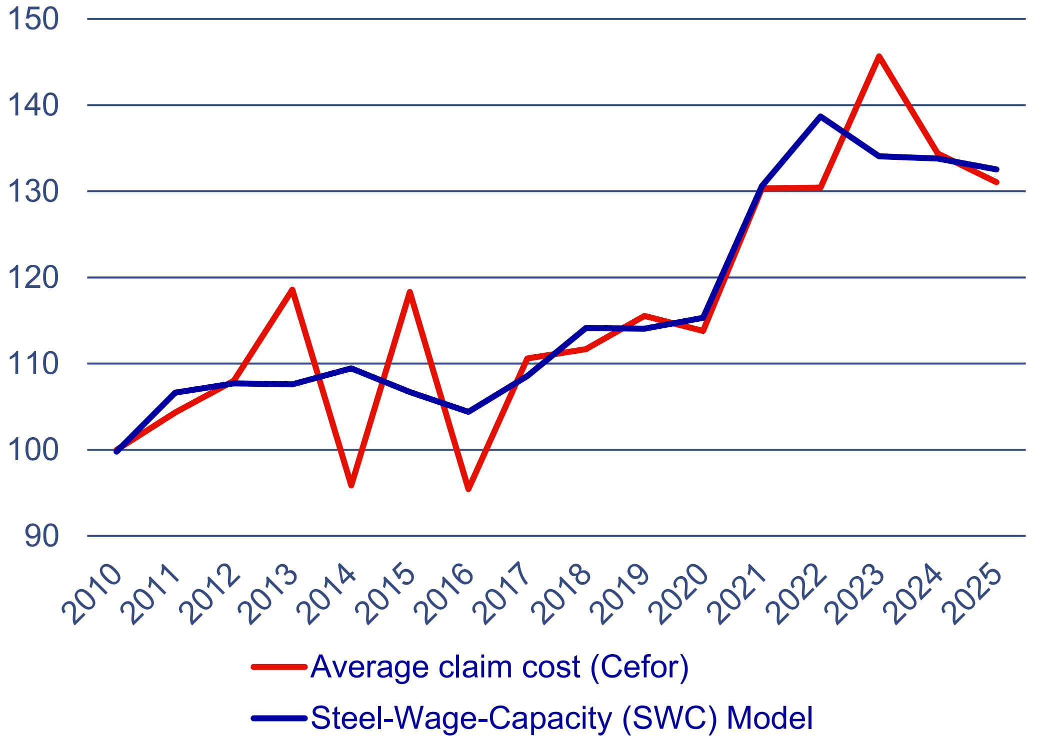

Figure 1 Comparison of indexed model output vs. benchmark claim data

Although not built primarily as a forecasting tool, the index structure can be extended to estimate future claims trajectories. A separate projection was developed using an Auto ARIMA time series model. This approach requires no manual parameter tuning and adapts to the statistical characteristics of the indexed claims data.

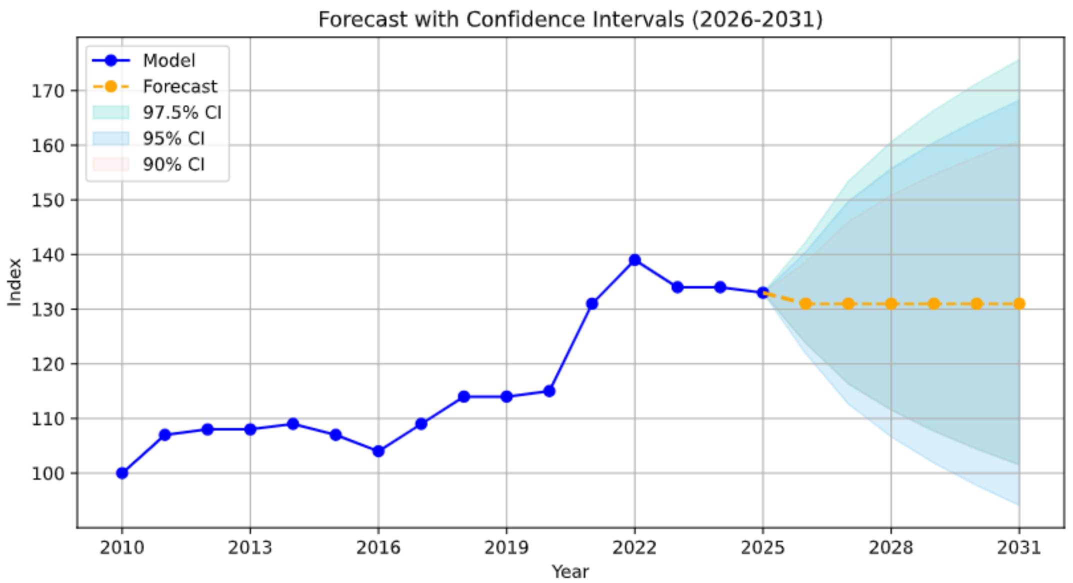

Figure 2 Forecast of Indexed Claims Cost using Auto ARIMA

The IUMI Hull Inflation Index provides a replicable, transparent framework for modelling structural cost development in hull insurance. While no model can replace detailed portfolio knowledge or local context, the index offers a valuable tool for internal monitoring, pricing discussions or macroeconomic scenario work.
Stakeholders are encouraged to adapt the index to their own exposures or regions and to engage with the IUMI Facts & Figures Committee for further dialogue and development.

Introduction and Motivation

The aim of this index is not to establish a definitive predictive model but rather to provide two alternatives for how repair cost inflation may be estimated within a robust analytical framework and open for discussion, analysis and further refinement. It is rooted in a strong belief in the value of open markets and international trade principles that the International Union of Marine Insurance (IUMI) has long stood for. By quantifying relevant macroeconomic and sectoral indicators, this index contributes to the understanding of structural inflationary trends in maritime risk management.
As marine underwriting increasingly relies on data - driven insights, tools such as this index support industry stakeholders in their decision making processes, enabling more informed risk pricing, reserving and strategic planning. The development of this index further aligns with IUMI's ambition to encourage transparency and dialogue across all facets of marine insurance practice.

Infobox – Terminology
Hull Claim Cost: The financial compensation paid by insurers for damages to the hull of a vessel.
Inflation Index: A statistical measure that tracks the changes in price levels over time, here applied to hull claim costs.
Benchmark: A reference value (here: average claim cost excluding total losses, Hull & Machinery insurance, provided by Cefor) against which the explanatory model is evaluated.

Framework and Influencing Factors

The average cost of hull insurance claims is shaped by a broad and heterogeneous set of drivers. These can be grouped into two categories: structural or contextual factors - some of which are difficult to quantify - and a second group of quantifiable economic variables that serve as the foundation for this index.
Among the less easily measurable factors are:

- Vessel Size and Complexity: Larger vessels often imply higher repair costs, not only due to material volume but also due to logistics, port requirements, and access to specialised facilities.
- Changes in Trade Routes: Geopolitical developments, climate - related passage openings, or regulatory shifts may lead to longer voyages or increased exposure to higher - risk regions.
- Technological Evolution: New shipbuilding technologies, fuel systems and automation create new repair challenges often increasing the cost and skill requirements for maintenance.

- Human Factors and Risk Culture: The competence level of crews and the safety culture onboard directly influence the occurrence and severity of incidents.
- Insurance Conditions and Legal Environments: Policy terms, liability scopes and the prevalence of social inflation - i.e. cost increases driven by broader legal and societal trends - can significantly impact the payout levels of claims.

While these variables are highly relevant, their direct measurement is not always feasible. This necessitates a focus on observable and quantifiable proxies which, though simplified, can still capture essential dynamics.

Among the measurable drivers, we identify three key components:

1. Steel prices, as a proxy for material cost in vessel construction and repair.
2. Wage levels in key shipbuilding and ship repair markets, reflecting labour input costs.
3. Shipyard capacity, as a bottleneck factor influencing availability and pricing of repair services.

These components were selected based on a combination of theoretical plausibility, data availability and empirical relevance. The next chapter will introduce each of these quantifiable drivers in detail and present the supporting data sources, processing methods and indexation procedures.

Quantifiable Drivers: Steel, Wages, and Shipyard Capacity

To develop a data driven and replicable index, three core components were selected based on their close theoretical connection to vessel repair costs and the availability of structured, long - term data: (1) steel prices, (2) shipyard - related wage levels, and (3) global shipyard capacity.

Steel Prices

Steel is a fundamental input in the construction and repair of vessels. Although ships consist of various materials and increasingly integrate specialised systems, steel remains the dominant structural component across nearly all commercial ship types. Consequently, fluctuations in steel prices directly affect the cost base for both newbuilding and repair activities.

For this index, we use a publicly available price series for “hot - rolled steel bars, plates, and structural shapes”, which has been indexed to a common base year to allow for time consistent comparison (see Figure 1). The index reflects global market prices (originally nominated in USD) compiled by the Federal Reserve (FED). Its strength lies in its broad industry acceptance and long historical time series.

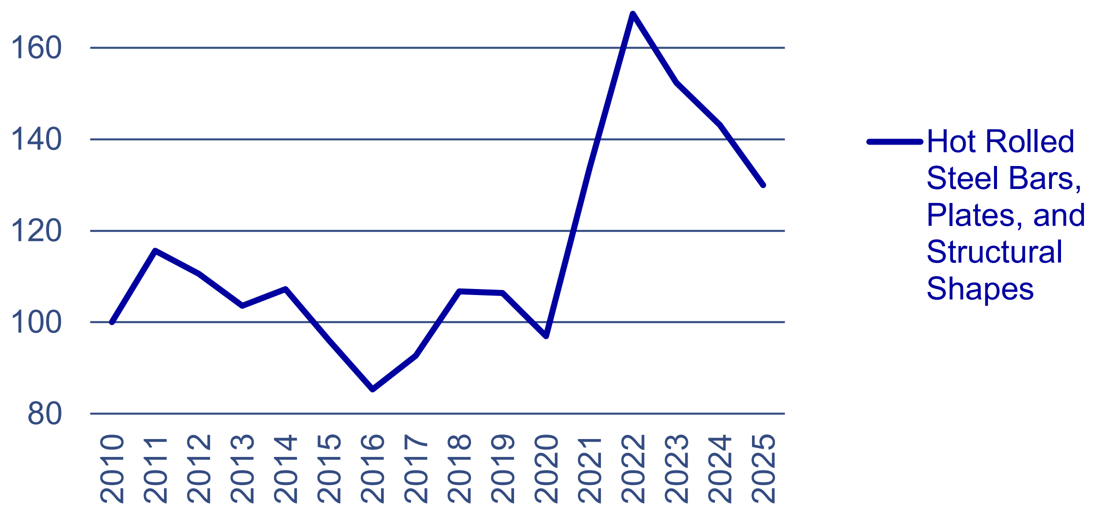

Figure 3 Indexed price of hot - rolled steel over time[1]

Wage Levels

Labour costs represent the second major component of vessel repair expenses. Over the past decades, shipbuilding and repair activity has shifted markedly towards East and Southeast Asia, particularly China, South Korea and to a lesser extent Japan. These countries have established global dominance in part due to lower labour costs, supported by large scale industrial infrastructure.

To reflect this shift, our model incorporates construction sector wage data from the main shipbuilding regions: China, South Korea, Japan and a composite group of European countries. Where possible, specialised wages (e.g. for boilermakers, welders and caulkers) are used; otherwise, broader sectoral wage indices are applied. All wage data are converted into USD terms using official exchange rates before being indexed. The resulting values are then weighted by each region's share of the global shipbuilding order book to reflect their relative importance in global repair capacity.

[1] source: https://fred.stlouisfed.org/series/WPU101704

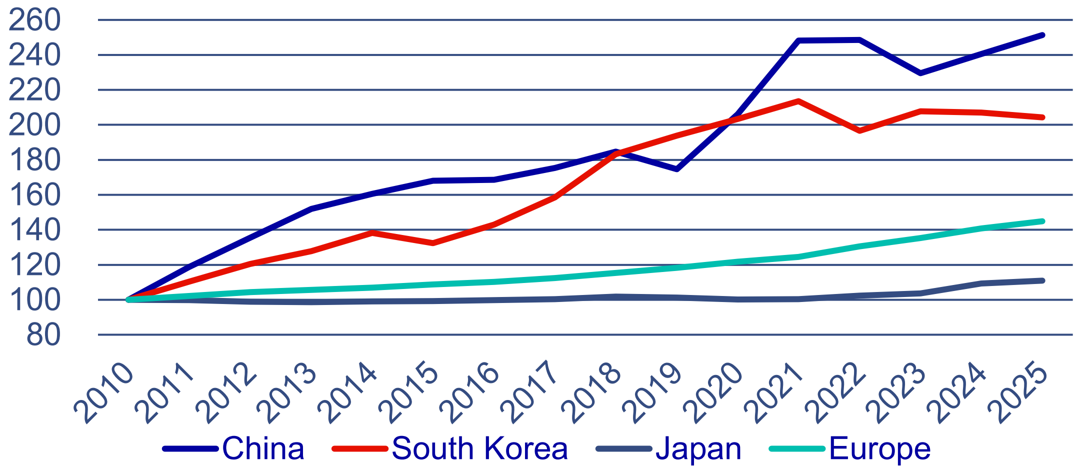

Figure 4 Indexed and weighted construction wages in key shipbuilding regions[2]

This regional weighting ensures that the index responds dynamically to structural shifts in shipbuilding dominance. For example, rising wages in China have a stronger effect than similarly rising wages in Japan due to China's higher global repair and newbuilding share.

Infobox: Weighting by tonnage built ships
The weighting of regional wage indices is based on each country's or region's percentage share of the vessels built (in gross tonnage). The data is available at Unctad.org. This approach ensures economic relevance and reflects market reality more accurately than equal weighting would.

Shipyard Capacity

A damaged vessel requires drydock access, skilled labour and a functioning infrastructure. Consequently, the availability of shipyard capacity becomes a constraint variable in the repair cost equation. However, shipyard repair capacity is notoriously difficult to measure as no comprehensive global or continuous datasets on national levels exist.
Three alternative approaches were evaluated for approximating shipyard capacity:

- **Option A:** Active building capacity minus annual deliveries (graphically available in annual report of BRS shipbrokers).
- **Option B:** Ratio of global order book to annual deliveries (interpreted as average delivery time).
- **Option C:** The *Global Order Book Forward Cover*, as published by Clarkson's Research.

[2] source China https://data.stats.gov.cn/,m source Korea: https://kosis.kr, source Japan: https://www.e-stat.go.jp, source Europe: https://data.ecb.europa.eu/

Option C was selected as the preferred proxy due to its consistency, availability and high correlation ($R^2 \approx 0.9$) with option B which seemed to be quite feasible. It represents the number of years required to clear the current order book based on the previous 12 month delivery rate. The forward cover functions as a dynamic indicator for yard capacity utilisation: higher values imply tighter capacity and potentially longer waiting times for repair slots.

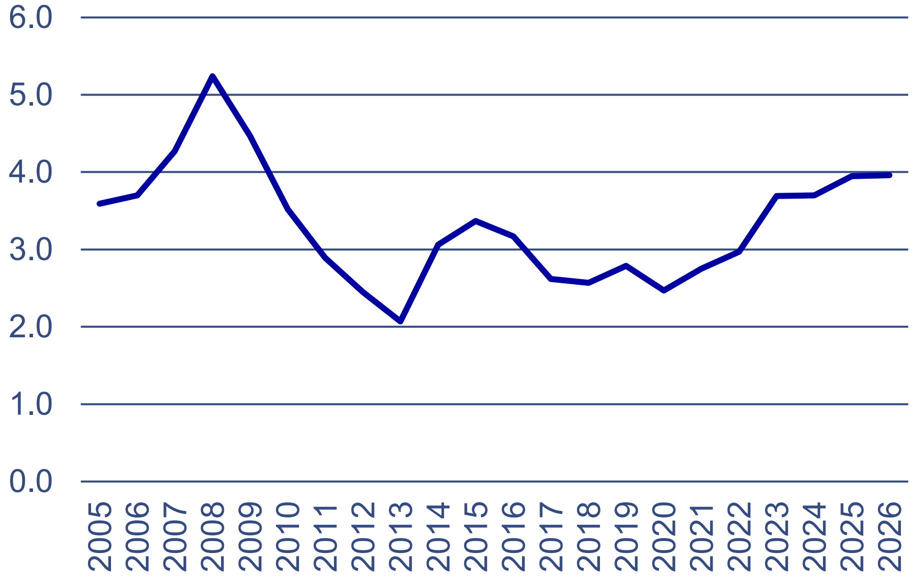

Figure 5 Forward cover index for global shipyards as a proxy for capacity constraints (Option C)[3]

Infobox: Understanding R² and Model Correlation
The coefficient of determination (R^2) measures how well a proxy or model variable explains variation in a reference variable. In this case, the R^2 of 0.91 between Options B and C indicates a very strong linear relationship justifying the use of the Forward Cover as a substitute for direct capacity measurement.

Model Construction and Methodology

Before constructing the model, the relationships among the three explanatory variables were examined to assess potential collinearity. Pairwise correlations show moderate positive relationships:

- Steel and wages: 0.69
- Wages and shipyard capacity: 0.38
- Steel and shipyard capacity: 0.38

These values indicate that the variables are interrelated but not redundant. Each factor contributes distinct information to the model while still reflecting shared underlying

[3] source: Clarkson's Research, February 2026

trends in global industrial and economic development. The moderate correlation levels suggest that multicollinearity is present but not severe enough to undermine model stability or interpretability. This interdependence is not surprising as increases in raw material prices, wage levels and capacity bottlenecks often occur simultaneously during periods of industrial expansion or cost pressure.

Having identified the three primary explanatory variables - steel prices, wage levels and shipyard capacity - the next step is to establish a model that links these drivers to the development of average hull insurance claims. The methodology follows a statistical regression based approach, designed to ensure transparency, replicability and robustness.
A Generalized Linear Model (GLM) was chosen for this task. Unlike ordinary least squares regression, a GLM allows for the specification of non-normal distributions and the use of link functions that better reflect the nature of the dependent variable, in this case the indexed average claim cost as provided by Cefor.

The Cefor data (Average claim cost, excl. total losses) was selected as the benchmark not only because they are currently the only available long-term time series on marine hull insurance claims, but also because they directly represent actual insurance costs borne by the market. To reduce statistical noise and improve the accuracy of cost development signals, the dataset was limited to claims exceeding USD 10,000. This threshold helps filter out deductible-level variations and minor events that may not reflect true shifts in repair costs, thereby enhancing the relevance of the series for inflation modelling purposes.

In this framework, the regress and (dependent variable) is the inflation-indexed average hull claim cost. The regressors (independent variables) are the three components introduced in Chapter 3. Each explanatory variable enters the model in its indexed, transformed and - where appropriate - weighted form. No manual assumptions are made about their relative importance; instead, the model infers their statistical contribution from historical data.
The resulting model equation can be written in simplified form as:

$$\widehat{Y_t} = \beta_0 + \beta_1 \cdot Steel_t + \beta_2 \cdot Wages_t + \beta_3 \cdot Capacity_t + \varepsilon_t$$

Where:

- $\widehat{Y_t}$: Estimated indexed claim cost at time t
- β_0: Intercept term
- β_1, β_2, β_3: Coefficients (weights) estimated by the model
- ε_t: Residual error term

The coefficients β_1, β_2, β_3 provide insight into the relative explanatory power of each driver. These weights are recalculated whenever new data becomes available, ensuring that the model remains adaptive to changing market dynamics.
This purely statistical approach offers several advantages over expert based weighting:

- It avoids potential biases stemming from subjective judgement.
- It allows for continuous updates as new data are added.
- It can be replicated or adjusted independently by other analysts using the same or alternative data sources.

Infobox: Why GLM and not OLS?
The Generalized Linear Model (GLM) extends the classical linear model by relaxing the assumption of normally distributed errors. This is particularly useful when modelling economic or insurance-related quantities, which may follow skewed or log-normal distributions. The flexibility of the GLM makes it a robust tool for real-world applications where assumptions of normality and homoscedasticity are often violated.

Benchmark and Goodness of Fit

To evaluate the explanatory power of the IUMI Hull Inflation Index, it is essential to compare the model results against a reference series of real world data. For this purpose we use an independently sourced benchmark: the indexed average hull claim cost provided by Cefor. This dataset serves as the *regressand* in the model and acts as a yardstick for model calibration.

The time series was indexed to a common base year to ensure comparability with the model's explanatory variables. All variables in the model (steel, wages, capacity) are also expressed in indexed form allowing for direct interpretation of co-movements over time.

The model was estimated using data from year T_0 to year T_n, with no artificial smoothing or outlier suppression applied. As a result, the model remains sensitive to real market phenomena including cyclical effects and shock years.
The GLM-based index shows a coefficient of determination (R^2) of approximately 0.83, indicating that roughly 83% of the variation in the benchmark can be explained by the three included drivers. While not perfect, this level of fit is strong enough to confirm that the model captures the dominant structural dynamics in hull claims cost development.

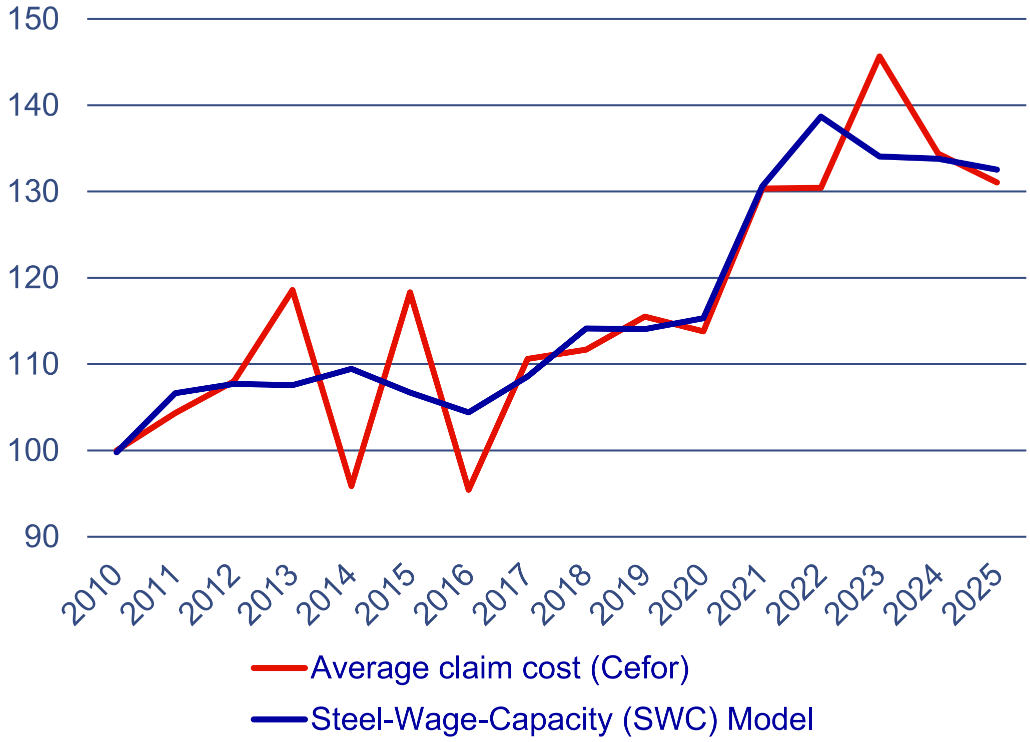

Figure 6 Comparison of indexed SWC model output vs. Cefor data

Visually, the model follows the benchmark curve with reasonable accuracy, particularly during periods of steady development. Deviations occur mainly in periods affected by one-off events or major losses - highlighting the limits of macroeconomic approximation when it comes to capturing operational volatility.
The model is intentionally designed to be robust but not overfitted. It does not seek to replicate every short term fluctuation but instead to reflect medium - to long - term cost developments based on real economic drivers. This makes it a suitable tool for scenario analysis, portfolio steering or internal pricing reference.

Infobox: Understanding R^2, Sample Size (n), and Model Interpretation
R^2 (Coefficient of Determination): Measures how much of the variation in the dependent variable is explained by the model. An R^2 of 0.87 means that 87% of the claim cost variation can be statistically attributed to the modelled variables.
n (Sample Size): Refers to the number of annual observations used in the regression. A larger n increases model stability and reduces the likelihood of spurious correlation.
Residual Analysis: A model with good fit will show small, randomly distributed residuals (differences between observed and predicted values), without persistent bias or drift.
Interpretation: A strong R^2 is helpful but not a guarantee of predictive power. Model performance must be interpreted in conjunction with domain knowledge and operational judgment.

Forecasting and ARIMA Projections

A natural extension of any explanatory index is the question of its forecasting potential. While the primary intention of the IUMI Hull Inflation Index is descriptive, it is methodologically relevant to assess whether the model can be used to anticipate future developments in average hull claim costs.

Initial tests with lagged GLM versions - where explanatory variables were shifted by one (t–1) or two (t–2) years - showed limited forecasting accuracy. This is largely due to the inherent volatility of the benchmark variable: in certain years, claim costs are driven by extraordinary events or sudden structural shifts that no macroeconomic variable can foresee. Consequently, a purely explanatory regression model lacks forward looking dynamics.

To address this, a separate forecasting module was developed using a timeseries based approach. Specifically, an Auto ARIMA (Auto - Regressive Integrated Moving Average) model was employed. This model type automatically identifies the optimal combination of lags and differencing parameters based on historical patterns in the dependent variable - in this case, the indexed average hull claim cost.
Using the full available time series, the Auto ARIMA model was trained and then used to project claim cost development over a multi-year horizon.

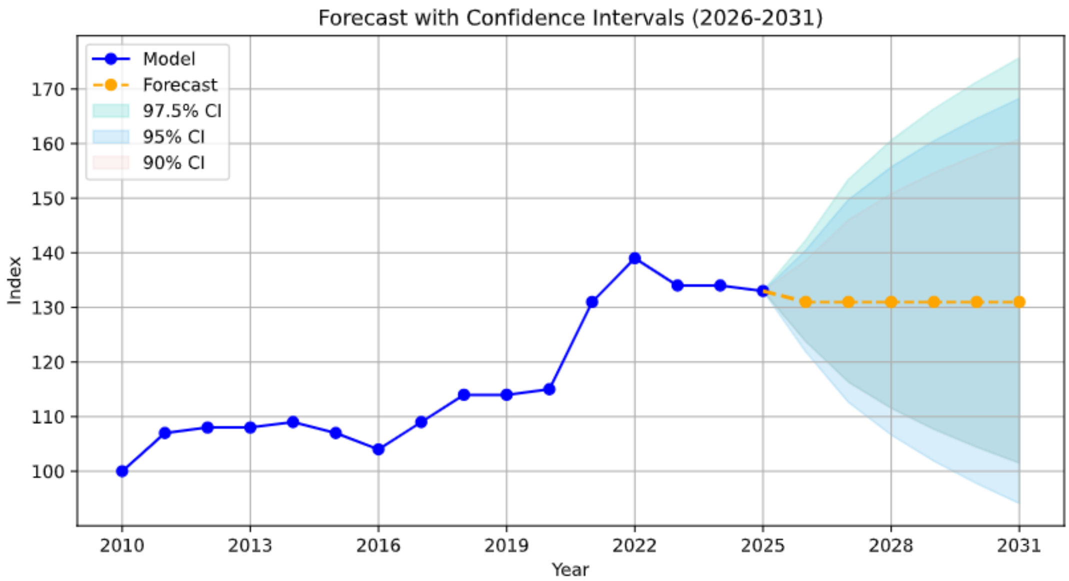

Figure 7 Auto ARIMA forecast of average hull claim cost with 90%, 95% and 97.5% confidence intervals

The model produces a fan chart illustrating the plausible range of future developments, depending on the confidence level:

- With a 97.5% confidence interval, the projected cost development ranges from a 40% decrease to a 40% increase over the next forecast window.

- With a 90% confidence interval, the range narrows to 27%.[4]

While this band is relatively wide, it reflects both the uncertainty of the global economic environment and the inherent noise in claim cost data. Importantly, the central tendency of the forecast suggests rising average claims in line with general inflationary pressure in materials, wages and repair capacity.

Infobox: Asymmetric Prediction Distributions
Prediction intervals are often assumed to be symmetric around the forecast, especially when based on normal distributions. However, in time series models like ARIMA, prediction errors can be asymmetric, causing uneven widening of confidence intervals. This can result from non-normal residuals, non-linear transformations (e.g. log scale), or model dynamics such as autocorrelation. In such cases, increasing the confidence level (e.g. from 90% to 97.5%) may cause the upper bound to rise more than the lower bound drops - or vice versa. This asymmetry means confidence intervals do not always expand uniformly and a narrower interval (e.g. 90%) can partially or fully overlap with a wider one (e.g. 97.5%) on one side. Awareness of this effect is essential when interpreting forecast uncertainty.

Conclusion: Auto ARIMA is particularly well suited for automated and repeatable forecasting applications but should be interpreted cautiously and validated against structural insights.

Outlook

The IUMI Hull Inflation Index provides a structured and transparent approach to understanding the cost dynamics of hull insurance claims in a changing global environment. By linking core macroeconomic drivers - steel prices, regional wage levels and shipyard capacity - to the development of average claim costs, the index offers both analytical clarity and operational relevance.

However, the framework is not without limitations. The model does not aim to capture every micro-level cost determinant, nor can it reflect all behavioural, legal, or technological influences at national or company level. Factors such as individual claims management practices, regional repair standards and contract negotiation dynamics lie outside the scope of this model.

Moreover, the global nature of the index means that it necessarily reflects averaged patterns which may not align with the experience of a single insurer, shipowner or market. Distinctive fleet compositions, risk cultures and trade geographies require adaptation or extension of the index to suit specific use cases.
This should not be viewed as a weakness but rather as an invitation to apply and tailor the model further. Stakeholders are encouraged to:

- Adjust the model to match portfolio specific exposure (e.g. fishing fleets vs container liners).
- Develop country - or region - specific indices using local wage and repair cost data.

[4] Please check the infobox below to learn why the lower bounds of 90% and 97.5% intervals are the same.

- Test alternative variables or functional forms to improve predictive validity.

Given the fluidity of today's economic and regulatory context - ranging from tariff shifts in materials such as steel to inflationary waves (as witnessed in 2021–2023), and geopolitical realignments of trade routes - an inflation index for hull claims must remain adaptive, explainable and open to scrutiny.

The IUMI Hull Inflation Index as presented in this publication is intended to support exactly that: a fact-based dialogue between underwriters, risk managers and analysts - grounded in data, guided by experience and refined through ongoing observation.

Stakeholders and interested parties are invited to reach out to the IUMI Facts & Figures Committee or the IUMI Analyst for feedback, collaboration and further development of this evolving analytical tool.