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Understanding and Predicting Maritime Industry Cyclicality

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ABSTRACT

Maritime transportation and insurance play pivotal roles in international trade. Both maritime and insurance industries are observed to follow cyclical patterns with recurrent upward and downward movements. This study examines the cyclicality of maritime freight markets and marine insurance premiums, assessing whether their cycles are synchronized. Using data from 1996 to 2019, including Baltic Dry Index (BDI) values and global hull insurance premiums, findings confirm significant cyclicality in both markets. Results indicate that hull insurance premium cycles lag freight market cycles by two years, with a common cycle length of 16 years. This synchronization has implications for risk management and policy-making.

1. Introduction.

Seaborne trade accounts for approximately 80% of global trade by volume and over 70% by value (United Nations Conference on Trade and Development (UNCTAD), 2022). Recent disruptions such as COVID-19, the Suez Canal blockage, and geopolitical conflicts have underscored the importance of maritime transportation. High inflation is one of the most important problems against global development. Interruptions of supply chains because of poor connectivity and logistics problems and higher freight prices are again contributing factors to higher prices of goods being shipped.

Shipping is one of the world's most capital-intensive industries, requiring a rough estimate of $80 billion per year to finance new vessels alone (Goulielmos and Psifia, 2006). According to a report by Allied Market Research (2021), the global shipbuilding market will be valued at $142.52 billion in 2020 and is expected to reach $195.48 billion by 2030, registering a compound annual growth rate of 3.2% during the forecast period. In addition to its transportation function, a ship is a shipping company's most important asset and investment vehicle. Operators bear the risk of the day-to-day operation and earnings of the vessels, while investors bear the risk of changes in the market value of the vessel, loan defaults and various international regulations. Thus, operators are mainly exposed to operational risks, while investors are exposed to market and financial risks (Yin et al. 2020). Due to the global nature of the business and the mobility of the vessel, maritime markets are exposed to exogenous factors such as political developments, global crises and international regulations. Despite all modern risk management methods, insurance is still an important, essential and reliable tool for parties exposed to these risks.

The price of risk in marine insurance is set by underwriters and depends on various factors, including the vessel's condition, client's loss history, management quality, navigation area, vessel type, cargo, and the experience level of crew. Underwriters consider the probability and monetary value of risks, past underwriting results, recent catastrophic losses, and market conditions influenced by capacity and congestion when calculating policy prices.

Maritime markets experience price fluctuations due to supply and demand factors. They are categorized into four main ar-

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eas: new building, second-hand (sale and purchase), demolition (scrap), and the freight market (Stopford, 2008). Transportation costs are largely determined by freight levels, which are sensitive to supply-demand imbalances. Freight levels serve as indicators of the maritime industry's health and can influence other markets sequentially (Beenstock and Vergottis, 1989a; Beenstock and Vergottis, 1989b).

Changes in demand for sea transportation, without significant alterations in capacity, directly impact transportation costs, influencing investors' profitability expectations and vessel prices in the short term. In the long term, capacity adjustments bring equilibrium, resulting in cyclical patterns in maritime markets. Ship prices are crucial for assessing total risk, particularly in property policies, leading to fluctuations in maritime freight affecting marine insurance prices similarly.

Despite the longstanding significance of maritime economics and marine insurance in global trade, academic research in maritime economics is relatively recent. Most studies on marine insurance focus on technical or legal aspects rather than economic ones. This research aims to address the gap by examining the cyclical movements in maritime freight and marine insurance prices and analyzing their interrelationship.

The paper is structured as follows: a review of related literature on maritime economics and marine insurance, followed by the research motivation and hypotheses, details on the data and methods, and results. The conclusion includes final remarks, limitations, and suggestions for future research.

2. Literature Review and Hypothesis Development.

The history of ships, trade, and related businesses is extensive and significant to global transportation. However, academic research in maritime economics is relatively recent, with notable growth following the 1960s, largely due to globalization (Heaver, 2012). Maritime transport is crucial for trade competitiveness, influencing the type, volume, and value of goods, as well as global supply chains (Valentine et al., 2013). Key developments include the shift toward emerging markets, transport costs, and the adaptation to ecological and social factors (Gilda, 2013).

Research in maritime economics primarily addresses freight markets and shipping finance, driven by the volatility of freight rates and the capital-intensive nature of the industry. Characteristics such as non-storable services and heightened sensitivity to global supply and demand make investment challenging, prompting significant academic inquiry (Alexandridis et al. 2018).

Key research areas include the interdependence of maritime markets and the influence of global economic changes. For example, Beenstock (1985) highlighted the connection between freight and ship markets and two subsequent studies by Beenstock and Vergottis (1989a, 1989b) applied this model for dry bulk and tanker markets. Kavussanos (1996) found that industrial production and bunker prices positively affect freight rates, while the stock of fleet has negative impacts. Results confirmed that the two most important sectors of world shipping - freight and ship markets - are interdependent, and the developments in one will spill over into the other. Grammenos and Arkoulis (2002) explored the relationship between shipping stock returns and global macro variables. Their results show that oil prices and laid up tonnage are negatively related to shipping stocks whereas the exchange rate variables are positively related. Bornozis (2006) examined how demand is shaped by global economic conditions and supply by the availability of global fleets, and that any imbalances between demand and supply have a direct impact on asset values, freight rates, and earnings. Li et al. (2018) analyzed interdependencies among different shipping markets, revealing one-way causality running from the dry bulk and clean tanker freight markets to the dirty tanker and container freight markets respectively. Moutzouris and Nomikos (2019) examined the relationship between ship prices, net earnings and holding period returns in the dry bulk industry. Results of the study show earnings yield to be a reliable indicator of the current condition of the shipping industry and future shipping market conditions. High earnings yield today reflects the current prosperous market conditions but also predicts deterioration in future net earnings and thus, future market conditions. Collectively, these studies underscore the complex interdependencies in maritime trade.

Cyclicality in maritime transport has been studied empirically by numerous researchers. Goulielmos and Psifia (2006) explain the significance of forecasting shipping cycles for successful investment timing. They employed Rescaled Range Analysis to determine the duration of shipping cycles, aiming for more successful shipping loans that could lead to a more stable market. Their analysis of 379 monthly observations from the trip dry cargo charter index between 1971 and 2002 revealed shipping cycles of approximately 4.5 years and 2.5 years, which were found to be non-periodic.

Chiste and Vuuren (2014) explored the cyclical behavior of the shipping market using Fourier Analysis on daily data of dry bulk freight earnings from January 1990 to October 2011. Over this 21-year period, they identified bimodal cyclicality, with a primary cycle of 7 years and a prominent cycle of 4 years. In contrast, Papailias et al. (2017) investigated the cyclical properties of the Baltic Dry Index (BDI) and constructed economic models to define these cyclical characteristics for accurate forecasting. They highlighted the economic significance of the BDI and suggested hedging strategies for market participants. Their trigonometric model explained 30% of the annual change in BDI over a span of 271 months from February 1993 to August 2015, revealing cycles of 3, 4, and 5 years and indicating a strong cyclical pattern. These studies focused on the dry bulk freight market and identified varying periods and characteristics of cycles. The differences may stem from the data periods analyzed or the methods used, but a common point is that dry bulk freight markets exhibit cyclical patterns.

Research on marine insurance from a maritime economics perspective is limited, despite its foundational role in the modern insurance industry. Instead, the literature is dominated by studies from insurance and law professionals. Aydemir (2010) defines terminology and specific features of marine insurance while exploring the factors critical for assessing risk and pricing strategies in the industry. The author notes that the global structure of the marine insurance industry is vital, as nearly all policies adhere to globally accepted laws and regulations. Risk sharing and transfer are more prevalent in marine insurance than in other categories due to the high monetary value involved. Pricing is as crucial in marine insurance as in any other industry for financial success and sustainability, and effective pricing requires accurate risk assessment and analysis.

Li (2017) discusses the role of marine insurance in ship finance, integrating financial, insurance, and legal perspectives. While marine insurance effectively transfers risk to the insurance pool, some risks remain uncovered due to fundamental rules and commercial unavailability. In addition to risk transfer, marine insurance can also lower capital costs, enhance liquidity for shipowners and shipbuilders, and provide reassurance for financiers.

As far as we know, no research explores the cyclicality of marine insurance, except for that conducted by Nieh and Jiang (2006). Their study focuses on the determinants of underwriting margins in the U.S. ocean marine insurance market and finds that the rational expectations hypothesis, as explained by Nieahus and Terry (1993), best fits this market. In marine insurance, prices are rational and reflect the expected value of future losses based on all available information; cycles arise due to long claims tails and reporting lags. The distinctive features of marine insurance, which differentiate it from other lines, include variations in coverage, exposure to risk, and regulations, making pricing in marine insurance more complex than in any other insurance line. The authors primarily examine the reasons behind cyclicality in the market and the periods of these cycles. They detail how cycles in the insurance business are influenced by past losses, market imperfections, regulatory and informational lags, past surplus, and interest rate fluctuations. The capacity constraint theory developed by Stewart (1984) and Bloom (1987) posits that changes in underwriting capacity drive these cycles. Real frictions and imperfections lead to a lack of capacity, negatively affecting the underwriting margin. Gron (1994) tested this theory, finding that variations in capacity significantly impact property-casualty insurance profitability, supporting the capacity constraint hypothesis. Unexpected decreases in capacity lead to higher future profitability and prices. However, Nieh and Jiang (2006) argue that the global nature of the maritime insurance business renders the capacity constraint theory inapplicable to this insurance line, considering the diverse factors at play.

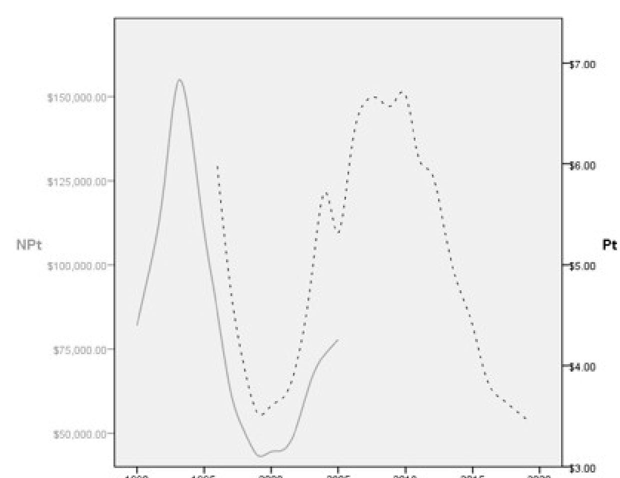
Research on marine insurance cyclicality is limited, but there is significant literature on cyclical behavior in insurance markets. Cummins and Outreville (1987) attribute this behavior to institutional and regulatory lags, while Berger (1988) suggests a feedback mechanism where profits impact surplus with a delay. Niehaus and Terry (1993) argue that insurers set premiums based on the present value of expected future losses, implying that price cycles emerge only if expected losses are cyclical, which is linked to market imperfections. Chen et al. (1999) identify underwriting cycles in the insurance industries of Singapore, Malaysia, and Japan, with varying lengths of 7.78, 12.01 and 13.86 years respectively.

Both maritime and insurance markets display cyclical characteristics driven by supply and demand and global macroeconomic conditions. The financial pricing/rational expectations theory (Nieh and Jiang, 2006) best explains cyclicality in marine insurance. This study aims to explore the relationship between maritime freight markets and marine insurance premiums by analyzing global hull and machinery premiums, BDI values, and world merchant fleet volumes from 1996 to 2019.

Key organizations like the Central Union of Marine Underwriters (CEFOR) and the International Union of Marine Insurance (IUMI) provide vital statistics on insured vessels, claims, and premiums. CEFOR focuses on Nordic markets, while IUMI covers the international landscape.

Figure 1 shows annual net average premium of a vessel insured in the Nordic marine insurance market with the available data CEFOR provided for the years in between 1990 and 2005 together with the average premium per deadweight tonnage (dwt) for the years in between 1996 and 2019 according to IUMI annual reports. An analysis of the annual net average premium for vessels in the Nordic market shows a clear cyclical pattern, with peaks in 1993 and 2010 and troughs in 1999 and 2019.

Figure 1: Annual net average insurance premiums of vessels.



Source: Net average premium per vessel for 1990-2005 (CEFOR annual reports 1990-2005) and average premium per dwt for 1996-2019 (IUMI annual reports 1997-2020).

Underwriting performance in marine insurance is closely linked to general economic conditions (Grace and Hotchkiss, 1995) and reflects trends in the maritime industry. Key factors influencing marine insurance pricing include the vessel's age, condition, and value (Aydemir, 2010), meaning that fluctuations in vessel values directly impact insurance rates.

The relationship between global macroeconomic conditions, shipping markets, and marine insurance can be summarized as follows: an increase in transportation demand, without a corresponding rise in fleet capacity, boosts maritime freight markets. This growth attracts investment, raises vessel demand, and consequently drives up both vessel and insurance prices.

Based on this understanding, the study proposes three hypotheses:

H_1: Maritime freight markets exhibit cyclical behavior.

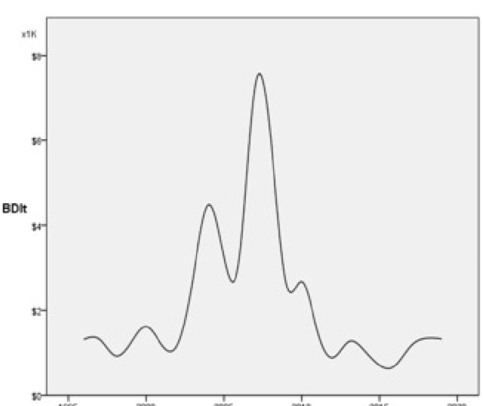
H_2: Marine insurance premiums demonstrate cyclical trends.

H_3: Maritime freight cycles and marine insurance premium cycles are positively synchronized.

3. Data and Methodology.

This study examines maritime freight markets using annual averages of monthly Baltic Dry Index values (BDI_t), as shown in Figure 2. Marine insurance is assessed through annual average premiums per deadweight tonnage (*dwt*), calculated by dividing total global hull premiums (HP_t) by the annual world merchant fleet volumes from 1996 to 2019. Data from IUMI's annual reports provides the total written global hull insurance premiums. Average unit hull premiums (P_t) are obtained by dividing total hull premiums by fleet volumes. To analyze cyclicality in global marine insurance, we use total written global hull gross premium data from IUMI, as CEFOR data is not available post-2005. Figure 1 highlights the concordance of these data sets.

Figure 2: Baltic dry index (BDI).



Source: Baltic Exchange (2020).

A fundamental method for identifying cycles in a time series is through the detection of turning points, first introduced by Burns and Mitchell (1946) and later refined by Harding and Pagan (2008). They define peaks as local maxima and troughs as local minima in the series ??$_{??}$. To identify cycles, one must locate these turning points and delineate the periods of expansion and contraction (Harding and Pagan, 2002). Harding and Pagan (2001) establish that a peak occurs at time t if the value is higher than those in a symmetric window of k observations on either side, while a trough is defined similarly but for lower values.

$$\begin{aligned} \text{Peak:}\;\; & y_t > y_s \;\text{ for }\; t-k < s < t \;\text{ and }\; t+k > s > t, \\ \text{Trough:}\;\; & y_t < y_s \;\text{ for }\; t-k < s < t \;\text{ and }\; t+k > s > t. \end{aligned} \quad (1)$$

To analyze cycles, the time series Y_t can be viewed as a trigonometric function made up of periodic components, represented by sine and cosine waves (Harding and Pagan, 2008). Papailias, Thomakos, and Liu (2017) applied this model in forecasting the Baltic Dry Index (BDI), examining periods of 3, 4, and 5 years. They compared a model using only cosine waves to a composite model that included both sine and cosine waves, finding that the composite model provided a better fit.

The model can be expressed as:

$$Y_t = \alpha + \sum_{j=1}^{m} \left\{ \beta_j \cos(2\pi\lambda_j t) + \gamma_j \sin(2\pi\lambda_j t) \right\} + \varepsilon_t, \quad t = 1, \ldots, T \quad (2)$$

In the formula above, the term λ_j indicates the horizontal stretch or in other words the frequency, β_j and γ_j control the amplitudes of the sinusoidal waves. It is possible to compare different cyclical time series and determine potential relationships between them by using these duration and amplitude statistics. The cyclical components of a time series can be analyzed based on how well periodic patterns align with the frequency of these models. Duration refers to the time it takes to complete one cycle, or the wavelength between two crests or two troughs.

When we identify these two measures of amplitude and duration, we can gain insights into the underlying patterns of the time series. When we detect these two measures of amplitude and duration which are perpendicular to each other on a graphic, the hypotenuse becomes the path followed by the variable (Harding and Pagan, 2008). Another important point to understand is whether the two cycles are in the same phases at an exact point of the time which shows the synchronicity of cycles.

To examine the synchronization of two cyclical series, it's beneficial to convert time series data into binary indicators of expansion (St=1) and contraction (St=0), following the methods of Burns and Mitchell (1946) and Harding and Pagan (2006). After identifying turning points, the cycle is divided into expansion phases (from trough to peak) and contraction phases (from peak to trough). This binary series effectively indicates which phase is occurring at any given time. SPPS (strong perfect positive synchronization) refers to the situation where the cycles are perfectly aligned. Strong non-synchronization (SNS) occurs when they move independently. Harding and Pagan (2006) use a moment method framework to analyze binary data from two cycles, focusing on unconditional and conditional densities. The authors set the moment conditions (3) and (4) for strong perfect positive synchronization null hypothesis and condition (5) for strong non-synchronized cycles null hypothesis.

$$\text{SPPS (i)}: \; E(S_{Y_t}) - E(S_{X_t}) = 0 \quad (3)$$

$$\text{SPPS (ii)}: \; E(S_{X_t}) - E(S_{X_t} S_{Y_t}) = 0 \quad (4)$$

$$\text{SNS}: \; E(S_{X_t} S_{Y_t}) - E(S_{X_t})\, E(S_{Y_t}) = 0 \quad (5)$$

The unconditional density of the two series is checked by applying (3) and conditional density is checked by applying (4). If both (3) and (4) are confirmed, the two series are perfectly synchronized. Rejecting (3) and/or (4) leads us to reject the strong perfect positive synchronization between the two cycles. If (5) is confirmed, it can be said that the series are strongly non-synchronized. Rejecting all three hypotheses shows that cycles are neither perfectly synchronized nor non-synchronized, but synchronized to a less than perfect degree. In this latter situation, examining the components of the correlation coefficient of the series (ρ_s) explained in (6) would be useful to check co-movement and interpret the degree of the synchronization (Harding and Pagan, 2006).

$$\rho_s = \frac{PrPr(S_{X_t}=1, S_{Y_t}=1) - [PrPr(S_{X_t}=1)\,PrPr(S_{Y_t}=1)]}{\sqrt{PrPr(S_{X_t}=1)\,PrPr(S_{X_t}=0)}\ \sqrt{PrPr(S_{Y_t}=1)\,PrPr(S_{Y_t}=0)}} \quad (6)$$

The current study uses the following test statistics Harding and Pagan (2006) propose for testing the two null hypotheses of strong perfect positive synchronization and strongly non synchronized cycles explained in equations (3), (4) and (5):

$$\text{SPPS(i)}: \ \hat{\mu}_{S_X} - \hat{\mu}_{S_Y}$$

$$\text{SPPS(ii)}: \ \hat{\rho}_S - 1$$

$$\text{SNS}: \ \hat{\rho}_S$$

Furthermore, Harding and Pagan (2006) define the concordance index exhibited in equation (7) as another measuring tool of the synchronization of cycles. The concordance index ($\hat{I}$) checks what fraction of the time the cycles are in the same phase.

$$\hat{I} = \frac{1}{T}\left\{\sum_{t=1}^{T} S_{X_t} S_{Y_t} + \sum_{t=1}^{T}(1-S_{X_t})(1-S_{Y_t})\right\} \quad (7)$$

The concordance index has a maximum value of unity when the contraction and expansion periods of studied time series overlap, i.e. $S_{X_t} = S_{Y_t}$ for all t. It will have a minimum value of zero when one series is in expansion the other is in contraction, i.e. $S_{X_t} = (1 - S_{Y_t})$ for all t. Hence, concordance index $\hat{I}$=1 corresponds to strong perfect positive synchronicity and $\hat{I}$=0 corresponds to strong perfect negative synchronicity. If the correlation between the two series is 0, then the concordance index becomes equal to 0.5 which means strong non-synchronicity between two series. In other words, the concordance index shows us the percentage of the time that cycles are in the same phase. Interpretation of the concordance index may be misleading in the instance that $\rho_s = 0$, so a prior check of the correlation between the two series is essential.

4. Data Analysis and Results.

4.1. Descriptive statistics.

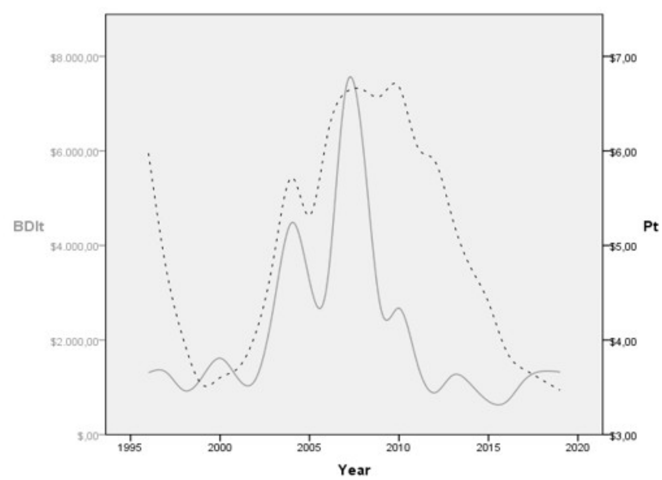
Table 1 presents the descriptive statistics of P_t, the unit hull premium per dwt in US dollars and BDI_t, the mean annual Baltic Dry Index values in US dollars. The mean value of P_t is 4.97 USD per dwt with a standard deviation of 1.16 USD per dwt, while mean for BDI_t is USD 2,127.22 with a standard deviation of USD 1,700.48 based on the data from 1996-2019. Skewness values indicate that P_t is more symmetrical (0.15) compared to BDI_t (1.88). Furthermore, P_t has lighter tails (kurtosis -1.54) than normally distributed data, while BDI_t (kurtosis 3.22) exhibits heavier tails. Overall, neither dataset follows a normal distribution. BDI_t demonstrates more pronounced peaks than P_t, whereas P_t is more symmetrical. Refer to Figure 3 for a visual comparison of both datasets.

Table 1: Descriptive statistics for P_t and BDI_t.

	P_t	BDI_t
Range	\$3.21	\$6,559.42
Minimum	\$3.47	\$692.83
Maximum	\$6.68	\$7,252.25
Mean	\$4.97	\$2,127.22
Standard Deviation	\$1.16	\$1,700.48
Skewness	0.15	1.88
Kurtosis	-1.54	3.22

Source: Authors.

Figure 3: P_t - BDI_t values among the years 1996-2019.



Source: Authors.

Despite both time series not being normally distributed, previous studies suggest that Pearson's correlation is the most suitable tool to measure the relationship between the two series (Harding and Pagan 2006, Chistè and van Vuuren 2014, Papailias et al. 2017). The results presented in Table 2 indicate a significant positive correlation ($\rho = 0.636$, $p = 0.001$) between BDI_t and P_t series.

Table 2: Correlation between P_t , P_{t+2} and BDI_t.

		P_t	P_{t+2}
BDI_t	ρ	0.636***	0.781***
	Sig. (2-tailed)	0.001	0.000
	N	24	22

*** Correlation is significant at the 0.01 level (2-tailed).

Source: Authors.

4.2. Identification of Turning Points

To identify turning points in the data series and assess cyclicality, Harding and Pagan (2002) used a window size of 'k'

equal to 2 for quarterly data. In this research, however, a symmetric window size of k equal to 5 yielded clearer results for annual data. Table 3 presents the peak and trough years of insurance premiums and freight rates using this approach.

Table 3: Turning points of P_t and BDI_t between 1996 and 2019.

	Peak	Trough	Peak	Trough
P_t	1996	1999	2010	2019
BDI_t	-	1998	2007	2016

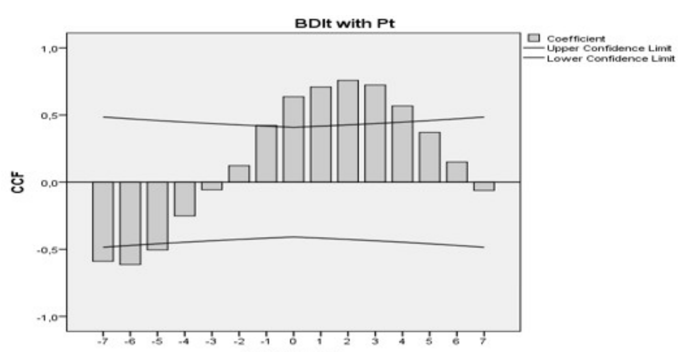
Source: Authors.

The analysis shows that from 1996 to 2019, there are one peak and two troughs for BDI_t and two peaks and two troughs for P_t. The first trough in BDI_t is one year before the first trough in P_t and BDI_t peak is three years ahead of the P_t peak. Second troughs have three years difference. There is an average two-year lag in turning points and this proximity of turning points suggest a positive relationship between the two series.

Only one clear completed cycle is identified both BDI_t and P_t during this period. Although the unit hull premium displays two cycles, the lack of data before 1996 complicates the classification of the first cycle. However, the peak and trough points indicate cyclicality in both series.

Detecting these turning points can aid in constructing a trigonometric model to analyze cycle periods and synchronicity. To further investigate potential lag in synchronicity, a cross - correlation analysis was performed, as illustrated in Figure 4.

Figure 4: Cross Correlation Coefficients.



Source: Authors.

The analysis of freight market rates (BDI_t) and hull premiums (P_t) reveals that the highest correlation of 0.758 (standard error = 0.213) occurs with a two-year lagged hull premium. Three-year lagged premiums show a correlation of 0.723 (standard error = 0.218), while one-year lagged premiums have a correlation of 0.708 (standard error = 0.209). These lagged correlations surpass the synchronous series correlation of 0.636 (standard error = 0.204).

4.3. Trigonometric Regression.

The model follows the formula (2) from Harding and Pagan (2008) and Papailias, Thomakos, and Liu (2017), using λ_j to represent cycle frequencies. Based on cross-correlation results, the analysis is applied to a two-year lagging hull premium series. Tests reveal a common cycle period of 16 years for both data series, with significant forecast models demonstrated through trigonometric regression, as summarized in Table 4. This approach confirms cyclicality in maritime freight markets and marine insurance premiums, supporting H_1 and H_2. The regression model is expressed as:

$$\widehat{BDI}_t = 2548.79^{***} - 2033.30^{***}\cos\left(\frac{2\pi}{16} * t\right) - 104.32\sin\left(\frac{2\pi}{16} * t\right)$$

$$\widehat{P}_t = 5.276^{***} - 1.286^{***}\cos\left(\frac{2\pi}{16} * t\right) + 0.932^{***}\sin\left(\frac{2\pi}{16} * t\right)$$

Table 4: Trigonometric Regression Results for BDI_t and P_t (standard errors).

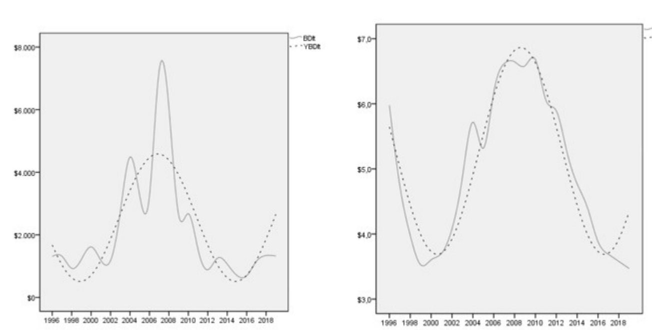
	$\widehat{BDI}_t$	$\widehat{P}_t$
Constant	2548.793***	5.276***
	(214.282)	(.082)
$cos\ 2\pi/16\ t$	-2033.304***	-1.286***
	(302.513)	(.116)
$sin\ 2\pi/16\ t$	-104.323	.932***
	(289.438)	(.111)
R^2	.684	.901
Adjusted R^2	.654	.892
No observations	24	24

*** Significant at the 0.01 level (2-tailed).

Source: Authors.

65% of the variation in BDI_t values and 89% of the variation in P_t are explained by the trigonometric model where the cycle duration is considered as 16 years. Although sine wave is not a significant variable for the BDI_t model, cosine wave is significant for modelling freight rates. However, both cosine and sine waves are explanatory in describing hull premiums. Figure 5 displays a visual representation of how well both models fit the data.

Figure 5: Trigonometric model fits of BDI_t and P_t.



Source: Authors.

4.4. Testing synchronization.

The duration of the cycles in P_t and BDI_t is approximately 16 years, as indicated by trigonometric regression results. While the cycle durations are the same, there is a significant difference in amplitudes. P_t values increase by about two times, whereas BDI_t values increase by over 10 times, indicating that BDI_t has a steeper trajectory.

Binary indicators S_{BDI_t} and S_{P_t} were created to perform synchronization tests using formulas (3), (4) and (5). These tests were conducted on both real-time data with no lag and data with a two-year lag, based on cross-correlation analysis results.

Table 5: Correlation between S_{P_t} , $S_{P_{t+2}}$ and S_{BDI_t}.

		S_{P_t}	$S_{P_{t+2}}$
S_{BDI_t}	ρ	.418*	.730***
	Sig. (2-tailed)	.042	.000
	N	24	22

*** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Source: Authors.

Table 5 shows correlation results for both applications, with and without lag. The correlation between the S_{BDI_t} and S_{P_t} (0.418) is significant at 5% level whereas the correlation between S_{BDI_t} and $S_{P_{t+2}}$ (0.730) is stronger and significant at 0.1% level.

Table 6: Synchronization test of S_{BDI_t} and $S_{P_{t+2}}$.

SPPS(i)			SPPS(ii)		SNS	
			$\hat{\rho}_S$- 1= -0.2697		$\hat{\rho}_S$= 0.7303	
$\hat{\mu}_{S_X}$- $\hat{\mu}_{S_Y}$	-0.04545		standard	robust (HAC adjusted)	standard	robust (HAC adjusted)
t	-0.29519	t	-1.77	-1.756	4.781	4.753
		s.e	0.1528	0.1536	0.1528	0.1536
p-value	0.7693	p-value	0.0928	0.0944	0.0001	0.0001

Concordance Index ($\hat{I}$) = 0.86

Source: Authors.

Table 6 shows the results of the synchronization test for S_{BDI_t} and $S_{P_{t+2}}$. *SPPS(i)* and *SPPS(ii)* cannot be rejected for the series S_{BDI_t} and $S_{P_{t+2}}$ ($p = 0.7693$ and $p = 0.0928$ respectively), while *SNS* is rejected ($p = 0.0001$). The correlation coefficient indicates strong positive synchronization between S_{BDI_t} and $S_{P_{t+2}}$ (Table 5). The concordance index ($\hat{I}$) shows that S_{BDI_t} and $S_{P_{t+2}}$ are in the same phase %86 of the time (Table 6).

Table 7 presents the results of the synchronization test for S_{BDI_t} and S_{P_t}. *SPPS (i)* cannot be rejected ($p = 0.7784$), while *SPPS(ii)* and *SNS* can be rejected ($p = 0.0058$ and $p = 0.0372$ respectively). Together with the less significant correlation coefficient and concordance index ($\hat{I}$) value slightly over 70%, analysis results confirm that there is positive synchronization between the series, S_{BDI_t} and S_{P_t}. Yet this synchronization is not as strong as the one found between P_t and BDI_{t+2}.

Table 7: Synchronization test of S_{BDI_t} and S_{P_t}.

SPPS(i)			SPPS(ii)		SNS	
			$\hat{\rho}_S$- 1= =-0.5819		$\hat{\rho}_S$= 0.4181	
$\hat{\mu}_{S_X}$- $\hat{\mu}_{S_Y}$	-0.04167		standard	robust (HAC adjusted)	standard	robust (HAC adjusted)
t	-0.2831	t	-3.0040	-3.0853	2.1589	2.22
		s.e	0.1937	0.1886	0.1937	0.1886
p-value	0.7784	p-value	0.0065	0.0058	0.0420	0.0372

Concordance Index ($\hat{I}$) = 0.71

Source: Authors.

With heteroskedasticity-adjusted standard errors, all correlation tests yielded the same accept/reject decisions, indicating that the results were robust. Analysis results confirm Hypothesis 3 which suggest a positive synchronization between S_{BDI_t} and S_{P_t}, however the findings show that the positive synchronization between S_{BDI_t} and $S_{P_{t+2}}$ is even more significant. The findings indicate a synchronized significant cyclicality between freight rates and hull premiums with a 2-year lag.

4.5. Forecasting Models.

Four forecasting models were formulated to predict hull premium values based on historical freight market rates. Table 8 summarizes all four regression models (A to D), along with the results of the trigonometric regression model (E).

The first three models (A to C) are simple linear regression models constructed using BDI_{t-1}, BDI_{t-2}, and BDI_{t-3}, respectively. These models demonstrate the signaling power of freight rates on future hull premiums. Among them, it is expected that Model B, which incorporates a two-year lag in maritime freight markets (BDI_{t-2}), has the highest R^2 value. Figure 6 illustrates the fit of Model B, which exhibits a strong explanatory power with an R^2 value of 61%.

The subsequent model (D) combines the values of BDI_{t-2}, the most significant *BDI* lag, with the trigonometric regression model. This model demonstrates the best fit among all the models considered with an adjusted R^2 of 0.890, as illustrated in Figure 7. Model D retains trigonometric variables significant for forecasting BDI cycles (see Table 4). However, including both BDI and trigonometric variables as dependents introduces collinearity issues, evident by the lack of statistical significance of BDI_{t-2} in model D. Ultimately, a model for marine insurance that merges the cyclical nature of premiums with maritime freight rates does not yield superior results. The trigonometric model (Model E) demonstrates 89.2% explanatory power and serves both to highlight cyclicality and as an effective forecasting tool.

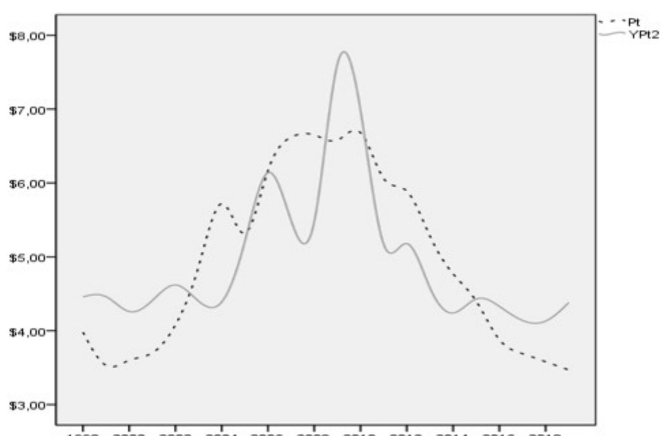
Table 8: Regression Results for hull premiums (standard errors).

	A	B	C	D	E
Constant	3.865*** (.279)	3.767*** (.265)	3.822*** (.285)	5.421*** (.259)	5.276*** (.082)
BDI_{t-1}	.0005*** (.000)	-	-	-	-
BDI_{t-2}	-	.0053*** (.000)	-	-0.000057 (.000)	-
BDI_{t-3}	-	-	.0051*** (.000)	-	-
$cos\frac{2\pi}{16}t$	-	-	-	.992*** (.168)	-1.286*** (.000)
$sin\frac{2\pi}{16}t$	-	-	-	-1.372*** (.195)	.932*** (.000)
R^2	0.526	0.610	0.581	0.906	0.901
Adjusted R^2	0.503	0.590	0.559	0.890	0.892
No observations	23	22	21	22	24

*** Significant at the 0.01 level (2-tailed).

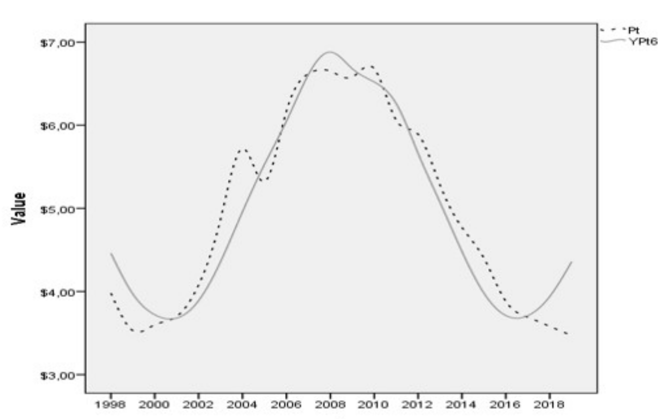
Source: Authors.

Figure 6: Model B fit - $Y_{P_t}=\alpha+\gamma BDI_{t-2}+\varepsilon_t$.



Source: Authors.

Figure 7: Model D fit - $Y_{P_t}\alpha+\beta cos(\frac{2\pi}{16}*t)+\gamma sin(\frac{2\pi}{16}*t)+\gamma_j*BDI_{t-2}+\varepsilon_t$.



Source: Authors.

Conclusions.

This study examines the relationship between marine insurance and maritime freight markets. It utilizes annual reports from the International Union of Marine Insurance (IUMI) and the monthly mean data from the Baltic Dry Index to analyze cycles in these markets by identifying turning points in the data series. The analysis of peaks and troughs indicated cyclical behaviour in both series, enabling further examination of the cycle characteristics.

The proximity of the turning points and the high correlation coefficient suggest a positive relationship between the two series, particularly with one to three years of lag. Cross-correlation analysis revealed the strongest correlation with a two-year lag applied to hull insurance premiums.

To evaluate the cyclicality and determine the cycle lengths, trigonometric regression was employed. The trigonometric models indicated a shared cycle between the Baltic Dry Index (BDI_t) and annual average premiums per deadweight ton (Pt), with a notable common 16-year main cycle between two-year lagged hull premiums and freight markets. This common cycle reinforces the positive relationship observed between the two series.

Although synchronization tests could not find a strong synchronization for unlagged freight markets and hull premiums, the test results of $S_{BDI_{t+2}}$ and S_{P_t} confirmed the presence of strong perfect positive synchronization (SPPS) between the lagged series, thus supporting the study's hypothesis of synchronized cycles in maritime freight and marine insurance premiums with a lag of two years in the premiums. The concordance index value indicates that the two series are in the same phase 86% of the time throughout the data period.

Additionally, four forecasting models are developed to estimate hull premiums (P_t) based on the *BDI* observations from prior years. Although all models proved significant, the model that provided the best fit incorporated BDI_{t-2} values alongside a trigonometric regression model. This two-year lag in the best-fitting model allows policymakers to plan in advance. The trigonometric model, on the other hand, reveals the cyclical nature of the market, identifies forthcoming peak and trough years, and serves as a useful forecasting tool. Together, the simultaneous use of both models offers deeper insights into the industry and equips policymakers with better strategies.

Despite the long and rich history of maritime transportation and marine insurance, no previous studies have explored the cyclicality of global marine insurance to uncover common cycles and explain the relationship between maritime freight markets and the marine hull insurance market, to our knowledge. This study clarifies the relationship between these two markets and constructs forecasting models that would benefit professionals in the insurance, international trade, and logistics industries, as well as investors.

The importance of this research is significant for professionals and key players in the maritime industry, including ship owners, charterers, insurers, and brokers. Additionally, traders may be indirectly affected by developments in these two markets, as changes in transportation costs can impact the prices of goods and raw materials.

The forecasting models developed in this study can assist these stakeholders in better assessing the current market situation, predicting future developments, and making informed decisions. Shipping is a capital-intensive industry, making budget planning essential for maintaining or improving competitiveness in the market. Consequently, these forecasting models would enable ship owners to estimate their insurance expenses more accurately and develop a more precise budget for the upcoming years.

Insurers can also benefit by making more accurate predictions about the marine insurance market by analyzing current trends in the freight market and adjusting their positions accordingly. Charterers, brokers, and traders can improve their forecasts and anticipate market changes by taking insurance prices into account as well.

All stakeholders, including investors, insurance companies, and insurance buyers, stand to gain from effective forecasting. Benefits include lower costs and prices, the ability to take advantageous positions based on market trends, and the development of effective strategies.

Risks are identified, measured, analyzed, and managed using appropriate techniques. The cyclicality examined in this paper indicates whether marine insurance market prices are high and helps determine if the insurance market is experiencing a hard or soft market stage. In hard market stages, insurance policies tend to be more expensive, and underwriting standards become stricter. During these periods, decision-makers may shift to risk retention strategies instead of relying on insurance risk transfer strategies.

This research enables decision-makers to understand the dynamics of the cyclicality of shipping revenues and marine insurance. When freight rates increase, insurance premiums also rise. As shipping companies see their revenues grow, they can afford higher insurance expenses and benefit from tax deductions associated with insurance. However, more expensive insurance policies can reduce profits for shipping companies.

Following the peak of freight rates, the revenues of shipping companies begin to decline. Despite this decline, insurance remains costly, and underwriting practices remain stringent. This situation does not last long; within two years, insurance companies start to lower their prices to attract shipping clients.

By analyzing the dynamics and overarching trends highlighted in this research, stakeholders—such as investors, insurance companies, and insurance buyers—can better assess the current market situation, anticipate future developments, and make informed operational and strategic decisions. This study indicates that the freight market reached its peak in 2007. The forecast model predicts a recurring cycle of 16 years, which accurately anticipated the downturn in freight prices observed after 2022, a trend visible in the current freight market. Additionally, the model forecasts a similar peak in insurance premiums expected in the following next two years, followed by a sequence of declines thereafter.

The primary limitation of this study was the restricted timespan of the available underwriting data, which only extends back to 1996. This lack of historical monthly or quarterly data in marine insurance constrains the analysis of potential sub-cycles within the main cycles observed in the data series. Furthermore, due to the global nature and inherent mobility of the maritime industry, a regional analysis was not feasible. Additionally, the inability to backtest the forecasting model was a significant drawback, as the data set only encompassed one complete cycle.

For further research, we recommend exploring the relationship between hull insurance prices and the conditions of other maritime markets, including newbuilding, sale and purchase, and demolition. Additionally, incorporating marine cargo insurance premiums and/or protection and indemnity (P&I) calls into this study could be beneficial. Given the lack of historical data prior to 1996, repeating this study in the future with additional data would allow for an assessment of the consistency of findings and models over time, as well as generate enough observations to backtest the forecast model.

Abbreviations.

BDI	Baltic Dry Index
CEFOR	Central Union of Marine Underwriters
DWT	Deadweight tonnage
IMF	International Monetary Fund
IUMI	International Union of Marine Insurance
UNCTAD	United Nations Conference on Trade and Development

References.

[1] Alexandridis, G., Kavussanos, M. G., Kima, C. Y., Tsouknidis, D. A., and Visvikis, I. D, (2018) A survey of shipping ?nance research: Setting the future research agenda. *Transportation Research Part E* 164-212.

[2] Allied Market Research (2021). Shipbuilding Market Size, Share, Report, Analysis, Growth - 2030 https://www.alliedmarketresearch.com/shipbuilding-market-A08511

[3] Aydemir, P. (2010). Deniz Sigortalarında Risk Değerlendirme (Unpublished master's thesis). Marmara University, İstanbul, Turkey.

[4]Baltic Exchange (accessed July 23, 2021). https://www.balticexchange.com/en/index.html

[5] Beenstock, M. A theory of ship prices. *Maritime Policy and Management*, (1985). 215-225.

[6] Beenstock, M., and Vergottis, A. (1989a). An econometric model of the world market for dry cargo freight and shipping. *Applied Economics*, 339-356.

[7] Beenstock, M., and Vergottis, A. (1989b). An Econometric Model of the World Tanker Market. *Journal of Transport Economics and Policy*, 263-280.

[8] Berger, L. A. (1988). A Model of the Underwriting Cycle in the Property/Liability Insurance Industry. *The Journal of Risk and Insurance*, 298-306.

[9] Bloom, T. S. (1987) Cycles and Solutions. *Best's Review: Property/Casualty Insurance*. 88: 20- 24

[10] Bornozis, N. (2006). *Dry Bulk Shipping: The Engine of Global Trade.* Capital Link.

[11] Burns, A. (1946). Burns and Mitchell on business cycles.

[12] Chen, R., Wong, K. A., and Lee, H. C. (1999). Underwriting Cycles in Asia. *The Journal of Risk and Insurance*, 29-47.

[13] Chistè, C., and van Vuuren, G. (2014). Investigating the cyclical behaviour of the dry bulk shipping market. *Maritime Policy and Management*, 1-19.

[14] Cummins, J. D., and Outreville, J. F. (1987). An International Analysis of Underwriting Cycles in Property-Liability Insurance. *The Journal of Risk and Insurance*, 246-262.

[15] Gilda, G. I. (2013). Changes in Global Economy Influencing the Maritime Industry . *ACTA UNIVERSITATIS DANUBIUS*, 246-258.

[16] Goss, R. (2003). Comment Maritime insurance and economic welfare. *Maritime Policy and Management*, 357-362.

[17] Goulielmos, A. M., and Psifia, M. (2006). Shipping finance: time to follow a new track? *Maritime Policy and Management*, 301-320.

[18] Grace, M. F., and Hotchkiss, J. L. (1995). External Impacts on the Property-Liability Insurance Cycle. *The Journal of Risk and Insurance*, 738-754.

[19] Grammenos, C. T., and Arkoulis, A. G. (2002). Macroeconomic Factors and International Shipping Stock Returns. *International Journal of Maritime Economics*, 81-99.

[20] Gron, A. (1994). Capacity Constraints and Cycles in Property-Casualty Insurance Markets . *The RAND Journal of Economics*, 110-127.

[21] Harding, D., and Pagan, A. (2001). Extracting, using and analysing cyclical information. Munich Personal RePEc Archive.

[22] Harding, D., and Pagan, A. (2002). Dissecting the cycle: a methodological investigation. *Journal of Monetary Economics*, 365-381.

[23] Harding, D., and Pagan, A. (2006). Synchronization of cycles. *Journal of Econometrics*, 59-79.

[24] Harding, D., and Pagan, A. (2008). Business cycle measurement. *Palgrave Macmillan (eds) The New Palgrave Dictionary of Economics*. London: Palgrave Macmillan.

[25] Heaver, T. D. (2012). The Evolution of Maritime Economics. In W. K. Talley, *The Blackwell Companion to Maritime Economics* (pp. 16-33). West Sussex: John Wiley and Sons Ltd.

[26] IUMI (accessed July 23, 2021). https://iumi.com/

[27] Kavussanos, M. G. (1996). Comparisons of Volatility in the Dry-Cargo Ship Sector: Spot versus Time Charters, and Smaller versus Larger Vessels . *Journal of Transport Economics and Policy*, 67-82.

[28] Li, C. (2017). Risk Management in Ship Finance: A Marine Insurance Perspective (Unpublished PhD Dissertation). University of Exeter, UK.

[29] Li, K. X., Xiao, Y., Chen, S.-L., Zhang, W., Du, Y., and Shi, W. (2018). Dynamics and interdependencies among different shipping freight markets. *Maritime Policy and Management*, 837-849.

[30] Moutzouris, I. C., and Nomikos, N. K. (2019). Earnings yield and predictability in the dry bulk shipping industry . *Transportation Research Part E*, 140-159.

[31] Nieh, C.-C., and Jiang, S.-J. (2006). Against Marine Risk: Margins Determination of Ocean Marine Insurance. *Journal of Marine Science and Technology*, 15-24.

[32] Niehaus, G., and Terry, A. (1993). Evidence on the Time Series Properties of Insurance Premiums and Causes of the Underwriting Cycle: New Support for the Capital Market Imperfection Hypothesis . *The Journal of Risk and Insurance*, 466-479.

[33] Papailias, F., Thomakos, D. D., and Liu, J. (2017). The Baltic Dry Index: cyclicalities, forecasting and hedging strategies. *Empir Econ*, 255–282 .

[34] Stewart, B. D. (1984). Profit cycles in property-liability insurance. *Issues in Insurance*, *2*, 95-98.

[35] Stopford, M. (2008). *Maritime Economics.* New York: Routledge.

[36] UNCTAD. (2022) *Review of Maritime Transport*. Retrieved from https://unctad.org/topic/transport-and-trade-logistics/review-of-maritime-transport

[37] Valentine, V. F., Benamara, H., and Hoffmann, J. (2013). Maritime transport and international seaborne trade. *Maritime Policy and Management*, 226-242.

[38] Yin, H., Chen, Z., Xiao, Y and Wang, S. (2020). Analysis of risk management performance with innovative approach: a case study of China's shipping companies. *Maritime Policy and Management*, 47:8, 1082-1096.