Systematic Risk Behavior in Cyclical Industries: The Case of Shipping

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Abstract

This paper explores macroeconomic and industry-effects on corporate systematic risk (beta) levels. We focus exemplarily on the international shipping industry to highlight the extent to which market betas may vary across regimes in cyclical industries and to analyze potential real determinants of systematic risk changes. Shipping firms operate in a strongly cyclical business environment and have been shown to carry extraordinary high degrees of financial and operating leverage providing an ideal case to study industry-specific beta behavior. We provide evidence for high levels of systematic risk in shipping stocks that match the corporate risk features of the industry. Key results indicate that shipping companies exhibit a strong industry cycle of risk compared to the average S&P 500 company reflecting the highly cyclical nature of the maritime business. Fluctuations in economic conditions and changes in industry-specific risk factors explain large proportions of this beta fluctuation in the cross-section and through time. Corporate managers should be aware of this fact when making capital budgeting decisions.

Keywords: Maritime financial management, equity beta, time-varying systematic risk, cost of capital

JEL Classification Codes: G30, G32

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I. Introduction

In modern finance beta is still the central concept to model and control for systematic risk in assets. Moreover, market beta is the key determinant of expected stock returns in the CAPM framework as well as in related common asset pricing models (Ross (1976), Fama and French (1993, 1995)), widely used by both academics and practitioners to compute a firm’s cost of equity. Given the concept’s importance for investors and corporate managers, it is crucial to ask how betas are determined. Contributing to the existing literature in this field, this paper provides evidence for a substantial industry component in individual systematic risk levels using the example of the highly cyclical shipping industry.

According to theory, market betas should reflect a firm’s incremental business risks at any point in time. Early studies emphasize that accounting measures of risk related to uncertainty in corporate cash flows are indeed positively correlated with systematic risk levels (see Beaver, Kettler and Scholes (1970), Logue and Merville (1972), or Melicher (1974) among others). This is further supported by more recent work of Campbell and Mei (1993), Campbell (1993, 1996), Campbell and Vuolteenaho (2004), and Campbell, Polk and Vuolteenaho (2009) who provide additional empirical evidence on this issue, consistent with the early results. Though these studies rely on cross-sectional analyses they support the view that varying cash flow risk levels are reflected in companies’ market beta. Using cross-sectional data, however, does not shed any light on the behavior of systematic risk through time and potentially time-related factors that might drive market betas.

Referring to the time-dimension of beta, Bos and Newbold (1984) argue that both changes in microeconomic factors (i.e. the business risk specific to the firm’s operations) and macroeconomic conditions (i.e. changes in global economic conditions or in industry-related factors) may affect systematic risk levels. This notion is closely related to the literature on beta fluctuation (Fabozzi and Francis (1978), Sunder (1980), Bollerslev, Engle and Wooldridge (1988), or more recently Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Lewellen and Nagel (2006)) and supported by early empirical studies (Robichek and Cohn (1974), Fabozzi and Francis (1979), Chen (1982)) as well as by recent theoretical work by

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1 See further Nickel and Rodriguez (2002) for a review on the accounting relationship between risk and return.
Gomes, Kogan and Zhang (2003). Basically, market betas tend to be higher during uncertain economic regimes. Thereby macroeconomic conditions may impact industries to a different extent. Notably, business cycle effects on systematic risk levels are expected to be stronger if the respective firms operate in sectors of the economy that exhibit a higher exposure to fluctuations in global business conditions. Isolating the cash flow impact on betas, i.e. beta effects associated with changes in expectations about future cash flows, Campbell and Mei (1993) document that cash flow induced risk in betas is substantially higher for cyclical industries. Also Fama and French (1997) show that beta volatility is different across industries. This indication of industry-dependent macroeconomics effects on beta is further supported by Gomes, Kogan and Zhang (2003) which provide model-based evidence for higher cross-sectional beta dispersion during weak economic conditions.

Following the existing literature both microeconomic and macroeconomic factors seem to affect market betas. However, to the best of our knowledge there exists no empirical evidence for the influence of industry characteristics on market betas in general. Overall, little is known about the behavior of market beat through time and its economic drivers. We focus exemplarily on the international shipping industry to highlight the extent to which market betas may vary across regimes in cyclical industries and to analyze potential real determinants of systematic risk changes. We rely on this specific sector for two reasons. First, given its incremental risk characteristics, the maritime sector provides an ideal case to study time-varying systematic risk. From the corporate finance perspective shipping is a highly leveraged, cyclical business with relatively high business risks. Given the close relationship between industry cash flows and the demand for seaborne trade, we expect that industry risk levels exhibit a strong correlation with global economic conditions which again would imply the existence of an industry cycle of systematic risk. Second, the shipping industry is one of the key sectors in the international economy, highly insufficiently studied in an asset pricing context. Commercial ships are involved in the carriage of roughly 90% of global trade and the availability, low cost, and efficiency of maritime transport has helped to facilitate the global division of labor as well as the shift of industrial production to emerging countries. However, high industry productivity levels are dependent on modern and efficient fleets and financing ships has become a severe task from the 2007 to 2009 global financial crisis on-
wards. Further, the ongoing industry crisis and Basel III regulations of banks have further lead to a lack of available bank financing for new vessels which corporates seek to compensate by tapping global capital markets. In this context, detailed knowledge about the level and the drivers of systematic risk levels is of eminent importance for managers. Precise estimates of the cost of equity capital are crucial in order to base investment decisions on reliable assumptions.

Asset pricing theory would suggest shipping companies to exhibit relatively high market betas compared to other industries reflecting the incremental business risks of the maritime business. In contrast to the commonly held conjecture that shipping companies feature above average risk characteristics, existing studies investigating the industry in an asset pricing context, have documented rather moderate equity betas. A list of empirical studies that explore the level of systematic risk in the shipping industry includes a series of studies conducted by Kavussanos and Marcoulis (1997a, 1997b, 1998, 2000a, 2000b), and one by Kavussanos, Juell-Skielse and Forrest (2003). Using standard OLS frameworks, these studies document close-to-unity betas for their samples of shipping companies, basically at odds with economic expectations. However, in the presence of beta fluctuation through time, OLS estimates would only provide an average indication of risk levels in the industry. Most recently, Gong et al. (2006) address this issue and investigate beta in the time-series dimension providing first indications of considerable systematic risk variation for sub-periods of their sample period. Their findings suggest that moderate industry beta estimates might be the result of switching high and low systematic risk regimes.

Our empirical analyses are based on a comprehensive dataset of 150 globally-listed shipping companies through the period from January 1973 through August 2014. Compared to prior industry studies, our dataset allows for detailed analyses of stock market betas in global shipping stocks both, in the cross-sectional and the time-series dimension, that do not suffer from sample selection or a limited sample period. Using a conditional CAPM framework, we obtain time-varying estimates of monthly betas and explore changes in industry risk levels through time. We find that systematic risk levels of shipping companies exhibit a strong industry cycle compared to the average S&P 500 company. Market betas fluctuate considerably
over the investigated sample period. Total industry annual beta averages vary between 0.583 and 1.292. The observed cycle pattern in risk levels is consistent over different industry segments. Supportive of prior evidence, we document that average market betas over the entire sample period have magnitudes around unity.

Our results suggest that moderate time-invariant market betas estimated in earlier work are indeed the result of time-varying risk levels. Depending on the time-period under investigation, shipping companies reveal to be substantially more (less) risky than the overall market. In line with expectations, estimated risk levels peak during the recent shipping crisis from 2007 onwards which led to severe turbulences in the maritime sector. The observed difference between time-varying and time-invariant beta estimates amount up to 0.5 for a given point in time (average industry estimate). In fact, this suggests that controlling for time-variation is crucial in the evaluation of corporate risk levels and capital budgeting relying on OLS-based cost of equity estimates may lead to suboptimal outcomes.

In a second step, our empirical analyses focus on the determinants of corporate risk levels. Based on the existing literature, we argue that both macro- and microeconomic but also industry conditions are expected to affect market beta. Using panel regressions including firm-specific, macroeconomic, and industry-related variables to explain observed systematic risk levels, we control for both cross-sectional and time-variation in market betas. Performed analyses describe the relative influence of the factor sets on industry risk levels and indicate that especially the latter two groups of factors explain large proportions of beta fluctuation. In contrast, firm-specific risk characteristics play a role in the determination of beta levels but do not provide a reasonable explanation for strong variation in market betas. These findings are robust after controlling for industry-segment effects and the institutional environment a firm operates in. Overall, our results indicate that systematic risk levels indeed reflect the cyclical nature of the international shipping industry implied through the close relation between the demand for seaborne trade and the business cycle. Corporate managers should be aware of this fact when making capital budgeting decisions.

The remainder of this study is structured as follows: Section II describes the sample selection procedure and reviews the data. Section III provides the theoretical framework for standard
beta estimation and presents first empirical results for time-invariant beta estimates. Section IV discusses the issue of time-variable market betas, introduces alternative estimation techniques and describes the behavior of systematic risk through time. Section V investigates the real determinants of systematic risk behavior. Finally, Section VI concludes.

II. Data and descriptive statistics

Our empirical analysis of systematic risk in the shipping industry is based on an international sample comprising 150 listed shipping companies from 35 countries which are chosen upon the primary condition that they own and operate commercial freight ships. Sample companies were identified using Thomson Datastream business descriptions as well as publicly available information from the companies’ websites and annual reports. This information set is further used to categorize the firms into different shipping segments. We sort the sample companies into four segments: "Bulk" (33 firms), "Container" (19 firms), "Tanker" (36 firms), and "Diversified" (62 firms), whereby the latter classification indicates that the company is active in two or more of the traditional shipping segments. Industry segments serve as indicators of intra-industry differences in operational activities that we control for throughout our analyses. Our sampling procedure eventually ensures that the sample only covers shipping companies in the classical sense of internationally operating freight shipping companies. We thereby explicitly exclude shipyards as well as shipping companies involved in passenger shipping, or those operating drilling ships, supply vessels, and inland vessels, since these companies are intrinsically different in the nature of their operations and arguably feature systematic risk characteristics that essentially differ from those of the core industry.

Monthly stock price data in US Dollar for all sample firms and monthly index values for the MSCI World value-weighted world stock market index (MSCI) are obtained from Thomson Financial Datastream. We calculate continuously compounded (total) returns for each sample firm and the MSCI as our proxy for the global market portfolio. Data on the Fama-French factor portfolios for size and book-to-market are from Kenneth French’s website at Dart-

\footnote{This category includes LPG shipping.}
mouth College. Risk-free returns are modelled using the one-month T-Bill rate from Ibbotson Associates. Annual accounting data used in the analysis of systematic risk determinants is obtained from Standard & Poor’s Compustat Global database. In order to ensure reliable estimation of market betas, we require firms to have at least 60 month (5 years) of consecutive non-missing stock return observations to be included in the final sample. Return data are winsorized at the upper and lower one percentile to mitigate the impact of outliers and to eradicate errors in the data. After all data cleaning steps, we remain with complete information for 29,014 firm-month observations. The sample period is January 1973 through August 2014. Summary statistics for shipping stock returns in our sample, as well as for the MSCI World, the risk-free asset, and the Fama-French benchmark portfolios are provided in Table I.

Notably, except for the diversified segment, average monthly shipping stock returns are slightly negative during the sample period. Compared to the MSCI, we further observe a relatively high volatility of monthly stock returns in all shipping segments as indicated by the measured standard deviation and the observed tail values (Min/Max). Quartile values of stock returns range from -8.1 percent (1st quartile) to 7.2 percent (3rd quartile). Although most related studies provide evidence for slightly positive average returns of shipping companies, these results are basically in line with the prior literature. Observed differences seem to be attributable to the different underlying sample periods. While prior studies rely on sample periods until 2006, our sample provides a more comprehensive picture also covering the drought years of the industry from 2007 onwards.

III. Estimating systematic industry risk levels: The time-invariant case

A. Methodological issues

The evaluation of systematic risk factors always includes the choice of an appropriate asset pricing model. Following the prior empirical literature, beta assessment throughout this study is mainly based on the standard approach in asset pricing: the capital asset pricing model

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3 See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library.
(CAPM). However, to provide broad initial evidence on systematic risk in the shipping industry, we further consider three other estimation approaches frequently applied in the related literature: the Fama and French (1993) model (FF model), as well as the methodologies proposed by Scholes and Williams (1977) and Dimson (1979). In this section, these models serve as indicators of time-invariant industry risk levels. Obtained beta estimates are compared across models and provide an indication of average systematic risk through the sample period, comparable with estimates from prior studies.

According to the CAPM of Sharpe (1964), Lintner (1965), and Mossin (1966), the expected return on an asset $i$ can be explained as a linear function of one single risk factor, i.e. the expected excess return on the market portfolio. This means that the following algebraic relation must hold for each asset $i$:

$$E[r_i] = r_f + \beta_i(E[r_m] - r_f)$$

where $E[r_i]$ is the expected return on asset $i$, $E[r_m]$ is the expected market return, $r_f$ is the risk-free rate, and $\beta_i$ is the asset’s non-diversifiable systematic risk in relation to the overall market risk which is defined as

$$\beta = \frac{cov(r_i, r_m)}{\sigma^2(r_m)}$$

A capital asset’s ‘true’ beta is not directly observable but can be approximated by the ‘empirical’ beta estimated from historical return data. Rearranging (2) and adding Gaussian white noise as well as a constant term $\alpha$ provides the following estimable formulation of the CAPM:

$$(r_{i,t} - r_{f,t}) = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \epsilon_{i,t}$$

Coefficient estimates for $\alpha_i$ and $\beta_i$ can be obtained for each asset via Ordinary Least Squares estimation (OLS) using a sufficient period of historical data. While the $\beta_i$’s measure the sensitivity of asset $i$ to changes in the expected return on the market portfolio (i.e. the asset’s systematic risk), the constant term $\alpha_i$ indicates deviations from equilibrium pricing. While ac-
According to the CAPM, pricing over the cross-section of stock returns would result in an $\alpha_i$, equal to zero for each asset $i$, a significantly negative (positive) $\alpha_i$ would imply that a stock is overpriced (underpriced) relative to its expected equilibrium price. That is, the expected return is higher (lower) than predicted by the CAPM implied securities market line (SML) of the asset universe. Equation (3) describes the base case formulation of the CAPM which all our key analyses rely on.

In the literature it is often argued that market risk as a single factor might be inappropriate to explain the cross-section of stock returns (Ferson and Harvey (1994), Fama and French (1993)). Fama and French (1993) account for this criticism regarding the validity of the CAPM and propose a three-factor model (FF model) in the spirit of Ross’s (1976) arbitrage pricing theory in which they extend the CAPM by to further factors, the difference between returns on small and large capitalization portfolios (SMB factor – small minus big) and the difference between returns on high and low book-to-market portfolios (HML factor – high minus low). They argue that higher average returns on small stocks and high book-to-market stocks reflect unidentified state variables that produce non-diversifiable risks in securities, not captured by the market return and priced separately from market betas. Based on this assumption, they formulate the following empirical model

$$
(E[r_{i,t}] - r_{f,t}) = \alpha_i + \beta_{1,i}(E[r_{m,t}] - r_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \varepsilon_{i,t}
$$

where, supplemental to the introduced notation, $SMB_t$ (small minus big) is the difference between the returns on diversified portfolios of small and big stocks for each time $t$, $HML_t$ (high minus low) is the difference between the returns on diversified portfolios of high and low B/M stocks, and $\beta_{2,i}$ and $\beta_{3,i}$ capture the co-movement of the asset $i$’s return with the added risk factors. Applying their factor model, Fama and French (1998) among others provide evidence against the single factor model and show that an international version of their model performs better than an international CAPM in describing average returns on portfolios formed on scaled price variables for stocks in 13 major markets. However, although FF model applications seem to outperform standard CAPM beta estimation in terms of model
accuracy, both approaches are still widely used in the academic literature as well as by practitioners to estimate stocks’ systematic risk and the corporate cost of capital.

Beside the debate of which risk factors should be included into an asset pricing model to provide the most reliable estimates for true beta, another strand of the literature has focused on estimation biases induced by asset-specific characteristics. Scholes and Williams (1977) and Dimson (1979) point out that non-synchronous trading of securities imparts a downward bias to the estimated beta when the underlying security trades infrequently. Moreover, Roll (1981) shows that the problem is particularly severe for smaller stocks. To assess whether our sample firms might be prone to potential thin-trading bias, we compare the average market capitalization in our sample with that of the average industrial firm from the Standard & Poor’s Compustat database. With an average market capitalization of 914 million USD, shipping companies reveal to be indeed relatively small compared to industrial firms (2328 million USD). Although the low average market capitalization may just serve as a proxy for thin-trading within our sample, we nevertheless decided to account for any potential bias in beta estimation arising from this issue and use the correction approaches proposed by Scholes and Williams (1977) and Dimson (1979) as a further indication of systematic risk levels in the industry. Both techniques are fairly straightforward. On the one hand, Scholes and Williams (1977) suggest the following beta adjustment that is computationally convenient but provides consistent estimates independent of detailed assumptions on the probability distribution underlying the sequence of non-trading

$$
\hat{\beta}_i^{SW} = \frac{\hat{\beta}_{t-1,i} + \hat{\beta}_{t,i} + \hat{\beta}_{t+1,i}}{1 + 2\rho_M}
$$

where \(\hat{\beta}_{t-1,i}, \hat{\beta}_{t,i}, \) and \(\hat{\beta}_{t+1,i}\) are market beta estimates from separate OLS regressions on the one-period lagged, the contemporaneous, and the one-period lead return of the market portfolio return and \(\rho_M\) ist he first-order autocorrelation coefficient of the observed market returns.

On the other hand, Dimson’s (1979) AC approach proposes to regress the return of stock i on the five lagged returns, the five leading returns, and the contemporaneous return of the market portfolio, eventually summing up the corresponding slope coefficients to obtain unbiased
beta estimates ($\beta_i^{Dimson}$). For the case with one lead and one lagged term $\beta_i^{Dimson}$ is exemplarily given by Equations (6) and (7).

$$r_{i,t} = \alpha_i + \beta_{i-1}r_{m,t-1} + \beta_{i,0}r_{m,t} + \beta_{i+1}r_{m,t+1} + \epsilon_{t,i}$$ \hfill (6)

$$\beta_i^{Dimson} = \beta_{i-1} + \beta_{i,0} + \beta_{i+1}$$ \hfill (7)

In his application Dimson (1979) uses five lead and five lag terms to calculate beta pointing out, however, that this should not be interpreted as a recommendation to use as many market terms in other empirical studies. In the absence of any reliable rule to determine the optimal number of leads and lags, we nevertheless decide to stick to this specification.

B. **Empirical results**

Existing empirical studies provide evidence of rather moderate systematic risk in the shipping industry reporting market betas around unity that fail to reflect the risk characteristics of an industry perceived to carry high financial and operating leverage and being exposed to a strongly cyclical demand for its products. Although other factors (e.g. the definition of ‘shipping companies’) may also have an impact on existing estimates, we conjecture that economically unintuitive results in prior studies might arise from a selection bias of two dimensions: (i) moderate sample sizes not representative for the entire industry and (ii) sample periods that do not include the years from 2007 onwards where the industry was hit by the most severe crisis in the history of shipping.

To obtain a starting point for our analysis of variation in systematic risk levels, this section compares existing evidence with the empirical results for our sample of internationally operating freight shipping companies. Table II shows time-invariant market beta estimates for the full sample period from January 1973 through August 2014. Firm-specific estimates for each firm are obtained via OLS estimation using the entire available data history of monthly stock returns. We report average CAPM, Fama-French, Scholes-Williams, and Dimson beta estimates for the overall sample and each shipping segment. Mean values are based on the beta estimates of the single firm. To document the substantial heterogeneity of carried market risk in our sample, we further provide average estimates for each market beta decile. Reported
standard deviations (SD) always refer to the intra-group distribution of beta (i.e. distribution of beta in the respective shipping segment or market beta decile).

[Insert Table II here]

Overall, mean beta values for all estimation methods are around unity which is so far not completely at odds with the prior literature, but indeed indicates moderate degrees of systematic risk in the industry. Regarding the segment averages, beta estimates for the full sample period range from 0.794 to 1.304 depending on the shipping segment and the estimation method. Highest market betas are observed for the bulk segment followed by container companies while tanker operators and diversified shipping firms show slightly lower exposure to the global market. However, except for bulker companies, observed estimates are quite homogeneous and differences seem to be economically insignificant. Thin-trading adjusted betas do not provide additional insights, though Dimson (1979) betas are slightly higher than standard OLS estimates. Anyway, reviewing the cross-sectional distribution of beta, the reported standard deviations of the estimated coefficients provide first indication for substantial heterogeneity in the cross-section. Reported mean beta values and standard deviations reveal that there are companies in each segment which carry high levels of risk compared to the overall capital market. This becomes even more obvious in the analysis of market beta deciles. We construct ten market beta bins according to the distribution of beta, separately for each estimation methodology and independent of the firms’ segment of operation.

Evaluating the distributional characteristics of the market beta deciles, provides a different view on the industries’ average beta. Most noteworthy, 30 percent of all sample firms show beta values significantly higher than unity for all approaches. Neglecting the Scholes-Williams results which seem to mark the lower bound of estimated systematic risk in our case, we can even constitute that 50 percent of the companies reveal betas larger than one. Looking at the upper and lower 20 percentile (i.e. 30 firms), the substantial heterogeneity across our sample firms becomes even more obvious. While the upper 20 percentile shows betas larger than 1.6, there seem to be firms in the lower quintile that reveal little exposure to the overall market. With beta values around 0.5, the systematic risk in such stocks seems to be relatively low. However, we constitute that, despite of substantial heterogeneity in the
cross-section of firms, average industry risk is still found to be more or less equal to that of the market portfolio proxy. In fact, being interested in the average industry level of systematic risk this means that perceived industry risks are not reflected in time-invariant market betas.

IV. Time-varying systematic risk levels

A. Methodological issues

Estimation approaches applied during this study so far have assumed beta to be constant over time. However, a large strand of the asset pricing literature has questioned the assumption of beta stability in general or by explicitly modelling time-varying systematic risk. Jagannathan and Wang (1996) study a conditional version of the CAPM and show that time-varying beta outperforms time-invariant formulations in explaining the cross-section of stock returns. Recent work further provides evidence for strong time-varying patterns of systematic risk over time (see e.g. Faff, Hillier and Hillier (2000), Lettau and Ludvigson (2001), Lewellen and Nagel (2006), and Mergner and Bulla (2008)).

By construction of beta it holds that if either the market volatility or its covariance with the asset’s returns is time-varying, then the beta will be time-varying. Referring to the time-dimension of beta, Bos and Newbold (1984) argue that both changes in microeconomic factors (i.e. the business risk specific to the firm’s operations) and macroeconomic conditions (i.e. changes in global economic conditions or in industry-related factors) may affect the comovement of stock returns and market returns. We will discuss this issue of driving forces behind beta in greater detail further below.

In order to model fluctuations in systematic risk levels of shipping stocks, we abandon the assumption of constant coefficients and refer to a conditional formulation of the CAPM in the

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remainder of this study. The applied framework for our tests is standard. In general, the time-varying CAPM is given by:

\[ r_t = \alpha_t + \beta_t r_{m,t} + \varepsilon_t \]  

(8)

where \( \alpha_t \) and \( \beta_t \) are now time-varying coefficients. Obviously, modelling time-varying beta is also conceivable in a multi-dimensional factor model context as proposed by Fama and French (1993). We nevertheless decide to perform these subsequent analyses on the basis of the single-factor CAPM for three reasons. First, our primary interest is on the market beta coefficient rather than on other factors that account for further risk dimensions. Second, we recognize that CAPM-based and FF-based betas are very similar when comparing our time-invariant results and conjecture that omitting other risk factors do not substantially bias our average estimates on market beta. Thirdly, and in line this, we prefer the CAPM from the econometric perspective as the most parsimonious among the available asset pricing models to minimize the parameters to be estimated in the dynamic framework.

In order to obtain time-varying monthly beta estimates, we apply three different estimation methods proposed by the literature: Kalman filtering (and Kalman smoothing), MGARCH-based beta estimation, and moving window OLS. Although existing studies have identified the Kalman filter to be superior in terms of in-sample predictive accuracy (Brooks, Faff and McKenzie (1998), Choudry and Wu (2008)), we nevertheless report results for all three methods for comparison reasons.

The Kalman filter approach involves formulating the CAPM in a state-space framework where the asset’s exposure to the overall market is considered to be an unobserved state variable following an underlying stochastic process. Explicitly, we assume beta to evolve according to a random walk. In this setting changes in beta are only expected if new information is available, i.e. \( E[\Delta \beta_t | \psi_{t-1}] = 0 \) with \( \psi \) being the information at a given point in time. Adapting this assumption for the underlying process of the intercept term provides the following state space framework which can be estimated using maximum likelihood and a Kalman filter:

\[ R_t = \alpha_t + \beta_t R_{m,t} + \varepsilon_t \]  

(9)
Following other applications of this approach (see e.g. Bollen and Whaley (2009)), we assume the error terms to be independent, homoscedastic, and serially uncorrelated, so that

\[
\begin{align*}
\alpha_t &= \alpha_{t-1} + v_t \\
\beta_t &= \beta_{t-1} + u_t
\end{align*}
\]

Departing from the initial state values, the Kalman filter provides recursive conditional estimates of the state variables \(\alpha\) and \(\beta\) for each time \(t\) up to \(T\). The basic Kalman filter refers to estimates of \(\beta_t\) based on information available up to time \(t\). In addition to the basic filter, we further apply the Kalman smoother which provides estimates for \(\beta_t\) based on all information available through the sample period. Following Harvey (1989b) we initialize the Kalman filter using arbitrary values for the state variables \(\alpha\) and \(\beta\) and corresponding covariance matrices with large diagonal elements that reflect the uncertainty of the initial values.\(^5\)

MGARCH-based modeling of beta throughout this study follows the approach introduced by Bollerslev (1990) which assumes a constant conditional correlation matrix when estimating the time-varying conditional covariance matrix of the variables of interest (i.e. \(r_i\) and \(r_m\)). The system of conditional mean equations is given as

\[
R_t = \varepsilon_t
\]

(11)

where \(R_t\) is a 2 \(\times\) 1 vector including \(r_{i,t}\) and \(r_{m,t}\) and \(\varepsilon_t\) is a vector of conditional errors defined to be \(\varepsilon_t|\Psi_{t-1} \sim N(0, H_t)\) with the conditional covariance matrix following a GARCH (1,1) of the form

\[
h_t = s + A\eta_{t-1} + G h_{t-1}
\]

(12)

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\(^5\) Results for repeated initializations with different values indicate that the series of states estimates is insensitive to the choice of the initial values.
where $h_t = vech(H_t)$, $\eta_t = vech(\epsilon_t \epsilon_t')$, and $A$ as well as $G$ are square parameter matrices. Further, $s$ is a parameter vector of proper dimension. According to Bollerslev (1990, the conditional variances and the covariance of the dependent variables are then given as:

\begin{align*}
    h_{11,t} &= s_{11} + a_{11} \epsilon_{11,t-1}^2 + g_{11} h_{11,t-1} \\
    h_{22,t} &= s_{22} + a_{22} \epsilon_{22,t-1}^2 + g_{22} h_{22,t-1} \\
    h_{12,t} &= \rho_{12} \sqrt{h_{11,t} h_{22,t}}
\end{align*}

Using the estimates for the conditional variances and the covariance between the return on asset $i$ and the market portfolio, beta estimates for each time $t$ can be obtained from Equation (2). Both approaches stated above are applied to estimate conditional beta series for each company in our sample. For comparison reasons, we also provide time-varying beta estimates from a rolling window OLS regression using a 60 months window.

**B. Empirical results**

We conjecture that moderate static beta estimates for cyclical industries may also be a result of variation in the stocks’ true market exposure over time. Suppose, for example, a firm has a high beta (e.g. 1.5) during one half of the sample period and a low beta (e.g. 0.5) during the other. In this case, OLS estimation would only reflect the average beta of the company which would be indistinguishable from that of the overall market although the stocks true beta reflects completely different risk characteristics.

Departing from this notion, the present section provides evidence for a time-varying systematic risk component in shipping stock returns. Using the outlined econometric approaches, we obtain point-in-time estimates of monthly beta for each time $t$ a firm provides market data on its stock in Thomson Datastream. Figure I depicts exemplarily the time-series estimates for ‘A.P. Møller - Mærsk A/S’, one of the sample companies that provides data over the full sample period from January 1973 through August 2014. Noteworthy, the time-series of rolling window estimates starts with a time-lag of 5 years due to the estimation window of 60

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6 Bollerslev (1990) explicitly assumes that the off-diagonal elements of $A$ and $G$ are equal to zero and that the correlation between the conditional variances of both variables is constant.
months. We further dropped the first 12 observations of the Kalman filter and Kalman smoother estimates to account for initialization of the filter algorithm.

[Insert Figure I here]

We recognize considerable cyclicality in all beta time series peaking during the recent years where the industry was hit by their most severe crisis in history. For comparison reasons, we also graph the static estimates as developed in Section III. As hypothesized, static beta estimates seem to describe more or less the average of the conditional time-series. To further investigate this issue, the following subsection compares static and conditional beta estimates for our full sample. To differentiate between static and dynamic models and to determine the best method in terms of the model’s ability to forecast observed stock returns, we subsequently perform in-sample tests for the predictive accuracy of each estimation technique. We finally use the conditional beta series to evaluate the behavior of systematic risk in the time dimension.

B.1 Comparison of static and dynamic beta estimates

Table III presents a summary of the conditional beta estimates for the full sample period from January 1973 through August 2014. We report average Kalman filter, Kalman smoother, rolling window, and MGARCH beta estimates for the overall sample and each shipping segment. Mean values are based on the lifetime average of monthly beta estimates of the single firm.

[Insert Table III here]

Similar to the one-company-example above, the conditional beta series reveal to have mean values close to the CAPM point estimate, both in the segmental and the overall analysis. The risk classification for the single segment remains unchanged. Bulk shipping companies still exhibit the highest levels of systematic risk, followed by tanker operators and the other two segments that still show relatively low risk measures. Among estimation methods, MGARCH produced the highest estimates. However, differences are of minor magnitude.

Regarding the distributional characteristics of the conditional beta series, we observe similar values for the market beta deciles as in the static analysis. Overall, the sample firms reveal to
have considerable heterogeneity in their market betas. Again, around 50% of the companies show average conditional beta values above unity. Notably, the MGARCH beta exhibits strong cross-sectional variation in the highest market beta decile.

B.2 Predictive accuracy of estimation methods

Although average values of all conditional beta series provide similar parameterizations of risk and closely match the static estimates on average, the graphical analysis from above suggests that dynamic estimates describe a different time behavior of systematic risk across estimation techniques (see Figure I). This observation is supported by non-tabulated correlation analysis revealing that pairwise correlation coefficients between the estimated beta time-series are substantially lower than unity. The extent to which the single correlation coefficients are less than unity suggests that the different modeling techniques in fact generate dissimilar results in the time dimension. Regarding the analysis of systematic risk behavior over time, however, we are interested in the model that best predicts observed stock returns in the present case. Further insights on the difference and similarities of the alternative approaches can be gained by estimating the in-sample forecast errors of each conditional beta series. We calculate mean absolute errors (MAE) and mean squared errors (MSE) to compare the predictive accuracy across the different approaches. Both may be calculated for the single firm i as

\[
MAE_t = \frac{1}{T} \sum_{t=1}^{T} |\hat{R}_t - R_t|
\]

and

\[
MSE_t = \frac{1}{T} \sum_{t=1}^{T} (\hat{R}_t - R_t)^2
\]

where T is the number of forecast observations and \(\hat{R}_t\) denotes the in-sample forecast of the return of firm i in period t based on the estimated model parameters. Since not provided by the MGARCH approach, we follow Faff, Hillier and Hiller (2000) and estimate the conditional intercept coefficient of each firm i for this model to be equal to the mean industry alpha given as
where $\bar{R}_t$ is the mean industry return at time $t$, $\bar{\beta}_t$ is the mean industry beta at time $t$, and $R_{m,t}$ is the corresponding return of the market portfolio.

Using these two measures of forecast errors, we analyze the performance of the different estimation techniques. To provide a comprehensive picture of the model performance in the given case, Table IV presents MAE and MSE values for both static and dynamic approaches.\(^7\)

[Insert Table IV here]

The reported results reveal that time-variable coefficient models are not generally superior to their static counterparts. Not surprisingly, the three factor FF model performs best among the static approaches. Moreover, it provides slightly lower errors than the rolling window model and the MGARCH approach, thereby dominating two of the dynamic models. However, though solely relying on the market factor to describe stock returns, the stochastic Kalman approach leads to overall superior results, with Kalman filtering yielding the lowest MEA and MSE values of all models both in terms of MAE and MSE for each segment and the overall sample. These results suggest that Kalman filter betas are the most reliable proxy for systematic risk in our sample. Subsequent analyses are hence performed on the basis of this conditional beta series.

### B.3 Evolution of beta through time

Departing from our finding that time-varying beta estimated via the Kalman filter algorithm best predicts the variation in shipping stock returns of our sample firms, we analyze fluctuations in Kalman filter betas in more depth. To assess the behavior of systematic risk over time Table V presents average annual beta estimates for the years 1990 through 2013, separately for each shipping segment and the entire sample.\(^8\)

[Insert Table V here]

\(^7\) For the Scholes and Williams (1977) approach the intercept term is assumed to be equal to the estimate from the regression involving the contemporaneous return of the market portfolio.

\(^8\) We exclude years prior to 1990 from this analysis to base results on a sufficient number of observations.
We note that beta exhibits considerable variation over the presented time period. This holds for all segments and the overall sample and is in line with our observation for the behavior of systematic of A.P. Møller - Mærsk A/S as displayed in Figure I. To further improve the accessibility of the results on beta variability, Figure II illustrates the evolution of beta as given by the numbers in Table V. We further add the average annual beta of all S&P 500 companies to provide a benchmark reflecting the average industrial firm.

[Insert Figure II here]

Obviously, beta reveals to have moderate levels in the early 90s, rather low levels at the end of the last century, and increases strongly in the beginning 2000s peaking during the years from 2007 onwards were the industry was hit by the most severe crisis in history. More precisely, all beta series show local maxima during 2008 and 2012/2013. These results suggest that systematic risk estimates indeed seem to reflect varying levels of industry risks. Further, it is inferable that beta exhibits a cyclical rather than a highly volatile behavior for all shipping segments that is different from the S&P 500 benchmark. Systematic risk levels between segments are relatively similar in low risk regimes, but differ to a certain extent in high risk regimes. Although levels of systematic carried in the single segment differ and risk shifting between the different segments can be observed during the sample period, all segments exhibit very similar risk patterns. We attribute this observation to an industry cycle of risk rather to a parallel shift in individual operational business risks of all sample companies and will investigate issue in the following section. Noteworthy, industry risk cycles based on single company estimates of beta have not been documented in the literature yet. Our results provide clear indication that individual systematic risk levels companies from a specific industry sector exhibit strong covariation.

V. Real determinants of systematic risk in the shipping industry

So far, our findings document considerable variation of systematic risk levels through time and in the cross-section of firms. Relatively large standard deviations for beta in a given year (see Table V) suggest that beta is not only dependent on time-related industry factors but is
also driven by other components that lead to different levels in systematic risk for the single firm in a given year.

In this section, we analyze which factors drive beta at the firm-level and which factors may account for the observed industry risk cycle. We build an empirical model for systematic risk in shipping stocks based on the prior theoretical and empirical literature and evaluate the relative importance of potential beta determinants in order to have a powerful model, able to explain the cyclical systematic risk behavior in the shipping industry.

A. An empirical model of systematic risk

In the 1970s and the beginning 1980s a strand of the asset pricing literature has turned to the analysis of the real determinants of systematic risk. The studies that attempt to provide insights on the real determinants of beta are numerous. Factors that have been taken into account in explaining the variation in observed beta include firm-specific as well as macroeconomic variables.

Following the seminal work of Beaver, Kettler and Scholes (1970), studies by Logue and Merville (1972), Breen and Lerner (1973), Rosenberg and Mc Kibben (1973), Melicher (1974), Ben-Zion and Shalit (1975), and Gahlon and Gentry (1982), among others, investigate the impact of financial accounting variables on the level of a company’s systematic risk. Though not mutually conclusive in terms of the reported effective directions, all of these studies provide empirical evidence that financial variables matter in determining beta. More recent work has put efforts on the decomposition of beta into different components related to specific source of risk (see e.g. Campbel and Wei (1993) or Campbell, Polk and Vuolteenaho (2009)). These studies provide further evidence that cash flow related risks drive beta at the company level.

Working in the same direction, a other studies have focused on the macroeconomic impact on systematic risk levels. Robicheck and Cohn (1974) and Chen (1982) study the inflation rate and real income growth as potential determinants of beta, but do not find a statistically robust relation that is in line with theoretical expectations. Moreover, Fabozzi and Francis (1979) provide support for a general business cycle effect on systematic risk levels. In another strand
of the literature, time-varying systematic risk levels have been estimated by accounting for influence of macroeconomic fundamentals (see e.g. Abell and Krueger (1989), or Andersen et al. (2005)).

However, existing empirical evidence is mainly based on cross-sectional analyses that do not account for the variation of beta through time. Borrowing from the prior literature, we build a panel model of systematic risk in the shipping industry, accounting for both cross-sectional and time-series variation of market betas. Pooling the existing evidence on the determinants of beta, we model systematic risk behavior as a function of firm-specific and macroeconomic variables that have been shown to influence risk levels in the cross-section, but further add an industry-specific time-varying factor that proxies for general uncertainty in the industry’s business conditions. We further control for stock exchange-related effects by including institutional variables that account for the financial system standards in the companies’ country of listing. Formally, beta is expressed as

$$\beta_{i,t} = X_{i,t} \gamma + F_t \delta + I_i \varphi + \varepsilon_{i,t}$$

(17)

where \( t \) describes the fiscal year-end month of firm \( i \) at year \( t \), \( \beta_{i,t} \) is the conditional estimate of beta for firm \( i \) at period \( t \), \( X_{i,t} \) is a vector of firm-specific financial variables, \( F_t \) includes macroeconomic factors, and \( I_i \) is a vector containing institutional characteristics of the country where the firm is listed. Further, the vectors \( \gamma, \delta, \) and \( \varphi \) include regression coefficients for the respective factor portfolios and \( \varepsilon_{i,t} \) is the error term.

In the following subsections, we specify the factor sets of firm-specific, macroeconomic, and institutional variables that are included in our systematic risk model and develop hypotheses how and through which channels they are expected to affect beta. We further provide construction principles of all variables. In general, we use annual accounting data from Compustat Global to calculate firm-specific financial variables for each year \( t \). Conditional beta estimates are those obtained through Kalman filtering as described in Section IV. Annual accounting data and monthly information on the level of a firm’s systematic risk are merged on a fiscal year-end basis. Thereby, we obtain a firm-year panel of systematic risk levels and firm fundamentals which we extend by macroeconomic and institutional indicators. Data
sources for the macroeconomic and institutional factors are manifold and described in the respective sections below.

A.1 Firm-level factors

Previous empirical studies investigating the impact of firm characteristics on systematic risk have examined different sets of financial variables. Beaver, Kettler, and Scholes (1970) chose seven financial variables; the study by Logue and Merville (1972) contains five financial variables; Breen and Lerner (1973) include seven explanatory variables while Melicher (1974) examined twenty-six variables, to name just a few studies that focus on the real determinants of beta. Beaver, Kettler and Scholes (1970) argue that though none of the frequently used accounting measures is defined in terms of covariance of returns, they are nevertheless expected to capture some of the uncertainty associated with corporate income streams. Assuming that the firm-specific factors are surrogates of the total variability of a firm’s return on common equity, they should reflect both systematic and idiosyncratic risk components and may hence account for partial variation in systematic risk levels of corporations.

Regarding our set of firm-specific determinants of systematic risk, we borrow from the existing literature and include the most commonly used variables into the linear regression model. We do not claim that this list is exhaustive, but we argue that it captures most of the important relationships suggested in the literature and reflects large proportions of the degree of uncertainty inherent in a firm’s business model. The list of factors includes: (1) operating leverage, (2) financial leverage, (3) corporate liquidity, (4) growth opportunities, (5) dividend payout, and (6) default risk.

Operating and financial leverage. Both operating and financial leverage have been identified to affect systematic risk in common stock of a company. Research that explicitly focuses on these two components of risk include Hamada (1972), Lev (1974), Chance (1982), and Hill, Stone(1980), and Mandelker and Rhee (1984). The latter provide a theoretical framework in which they show that the degrees of operating leverage (DOL) and financial leverage (DFL) play an important role in investigating the impact of asset structure and capital structure on systematic risk. They highlight that both magnify the intrinsic business risk of a company. In line with prior empirical results by Hamada (1970) and Lev (1974), their empirical findings
suggest that DOL and DFL explain a large proportion in the variation of beta, both having a positive relation. Based on this evidence we expect DOL and DFL to be important in determining the level of a company’s systematic risk.

In measuring operating and financial leverage, we follow the approach suggested by O’Biren and Vanderheiden(1987) that has been frequently applied in the recent literature. They suggest to estimate DOL and DFL through a two-step time-series regression that explicitly accounts for time trends in the respective accounting data. The first step includes running the following three regressions:

\[
\ln(EBIT_t) = \ln(EBIT_0) + g_{ebit}t + \mu_{t,ebit} \tag{18}
\]

\[
\ln(SALE_t) = \ln(SALE_0) + g_{sales}t + \mu_{t,sales} \tag{19}
\]

\[
\ln(EAIT_t) = \ln(EAIT_0) + g_{eait}t + \mu_{t,eait} \tag{20}
\]

where \(EBIT\) is earnings before interest and tax, \(SALE\) is sales, and \(EAIT\) is earnings after interest and tax. Equations (18), (19), and (20) can be easily estimated via OLS regressions of the logs of \(EBIT\), \(SALE\), and \(EAIT\) on time. Once the residual series \(\mu_{t,ebit}, \mu_{t,sales},\) and \(\mu_{t,eait}\) are obtained from these regressions, in a subsequent step, DOL and DFL can be estimated from the following equations:

\[
\mu_{t,ebit} = OL \mu_{t,sales} + \varepsilon_t \tag{21}
\]

\[
\mu_{t,eait} = FL \mu_{t,ebit} + \theta_t \tag{22}
\]

where \(OL\) and \(FL\) are regression coefficients providing the estimates for DOL and DFL. \(\varepsilon_t\) and \(\theta_t\) are Gaussian white noise. Following this approach DOL measures the average sensitivity of (i) the percentage deviation of earnings before interest and tax from its trend, relative to (ii) the percentage deviation of sales from its trend, while DFL measures the average sensitivity of (iii) the percentage deviation of earnings after interest and tax from its trend, relative

\[9\] For a recent application in the context of operating leverage see e.g. Garcia-Feijoo and Jorgensen (2010).

\[10\] To compute logs of negative earnings \(EAIT\) and \(EBIT\), we follow Ljungqvist and Wilhelm (2005) and use a transformation common in accounting research which is given for earnings before interest and tax as: \(\ln(1 + EBIT_t)\) if \(EBIT \geq 0\) and \(-\ln(1 - EBIT_t)\) if \(EBIT < 0\).
to (iv) the percentage deviation of earnings before interest and tax from its trend. Using the respective data items from Compustat Global, we estimate Equations (21) and (22) at five-year overlapping intervals at the firm level to end up with parameter estimates on DOL and DFL at the end of each fiscal year and for each firm.

**Corporate liquidity.** On the one hand, it can be argued that current or liquid assets provide less volatile returns than non-current assets. Beaver, Kettler and Scholes (1970) use the example of cash as the most liquid asset to highlight that, in the extreme case and ignoring purchasing power parity, current assets may have an expected return of zero with zero volatility. Given it holds that current assets have less volatile returns, one would expect firms with larger proportions of current assets to have less volatile overall equity returns and correspondingly lower levels of systematic risk. On the other hand, but in same direction, firms with a higher liquidity ratio may ceteris paribus be more flexible in crisis periods and less sensitive to fluctuations in the economy. This would lead to a lower beta by construction. We test for the influence of liquidity on systematic risk by including a firm’s current ratio defined as current assets divided by current liabilities into our model.

**Growth opportunities.** Prior empirical studies investigating the association between systematic risk and growth have generally hypothesized and observed a positive correlation between risk and growth in assets or growth in earnings, respectively. In another way, growth can be defined as investment in new projects with higher expected returns and correspondingly higher risk that lead to a change in the firm’s current business risk. Further, growth firms may also face higher levels of market competition than their mature counterparts. In the end, both an expected increase in investment into new projects combined with an expected increase in competition might result in higher levels of systematic risk in a company’s common stock. Based on the forward looking nature of capital markets, we focus our analysis on growth opportunities rather than observed growth. We model growth opportunities using the market-to-book ratio of a firm, arguing that growth firms are expected to have higher market-to-book ratios on average. Specifically, we define a dummy variable indicating high growth firms. A company is classified as a “high growth firm” if its market-to-book ratio is part of the upper thirty percentile in a given year.
Dividend payout. The payout ratio of firms has been used in numerous tests of association with beta. Most prior studies indicate a negative relation between dividend payment and the level of systematic risk. Beaver, Kettler and Scholes (1970) and Bowman (1979) point out that dividends may not directly affect beta but do convey information regarding future earnings to the market. The former argue that, given firms pursue a policy of dividend stabilization, a high payout ratio today might be viewed as a signal for the management's perception regarding the uncertainty of future income streams. The argument is supported by empirical evidence showing that dividend payout adjusted for comovement with earnings does not have any impact on systematic risk. That is, one would expect dividend payout to be negatively correlated with beta. We operationalize the payout ratio as dividends paid plus share repurchases divided by total assets sorting firms into high dividend and low dividend firms. A firm is classified as a high dividend payer if its payout ratio is in the upper thirty percentile in a given year.

Default risk. A large strand of the empirical literature deals with the question whether default risk is systematic. Several studies suggest that corporate default risk could be behind the size and book-to-market effects (see among others Dichev (1998), Vassalou and Xing (2004)). However, empirical evidence on this issue is ambiguous. While Dichev (1998) does not find any significant relation between the probability of default and the cross-section of stock returns, results in Vassalou and Xing (2004) show that both Fama-French factors reflect large proportions of default risk. This latter finding supports evidence provided by Lang and Stulz (1992) and Denis and Denis (1995) which both show that the probability of default is related to aggregate macroeconomic factors and hence might be systematic. This is further supported by recent work of Benmelech and Bergman (2011) which suggest an intra-industry collateral channel through which bankrupt firm impose negative externalities on their non-bankrupt peers. The argument is that one firm’s bankruptcy increases the likelihood of asset fire sales and will place downward pressure on similar assets. This issue might be especially severe in asset intensive industries (see also evidence by Pulvino (1998)). Following this argumentation, we hypothesize that the probability of a corporate default is an underlying firm-specific but industry-related driver of beta and control for the probability of bankruptcy in our systematic risk model. Using Altman (1963) z-scores, we separate firms into groups with high
(low) bankruptcy probability. Specifically, a firm is classified as having a high probability of bankruptcy if its z-score is in the upper thirty percentile in a given year.

A.2 Macroeconomic factors

Beside the firm-level factors, our systematic risk model also includes macroeconomic variables which attempt to account for levels of uncertainty induced by the overall economy. Prior literature that has examined the effect of economic conditions on the stationarity of beta coefficients is scarce and empirical evidence is not convincingly conclusive. To the best of our knowledge, only Robichek and Cohn (1974), Fabozzi and Francis (1979), and Chen (1982) investigate this issue in more detail. While Fabozzi and Francis (1979) provide evidence for a general unspecified link between the business cycle and systematic risk components in stock returns, the other two study beta as a function of inflation and real income growth. However, results indicate ambiguous effects for both factors. Abell and Krueger (1989) show that interest rates, budget deficits, trade deficits, inflation, and oil prices influence changes in beta. Probably most related to our approach, Andersen et al. (2005) use a state-space framework to model systematic risk levels where macroeconomic variables directly impact the underlying stochastic process of beta. They find that industrial production growth is positively correlated with market betas.

In our study, we use five macroeconomic factors to control for broader economy-related effects in systematic risk: (1) freight rate volatility, (2) industrial production growth, (3) inflation rate, (4) credit spread, and (5) exchange rate volatility. These variables reflect industry-specific and global macroeconomic risk factors.

Based on the observed industry cycle in systematic risk (see Figure II), we argue that industry-specific factors are expected to be important drivers of shipping companies’ beta. Among other factors, freight rates that are closely tied to the supply/demand balance on global freight space can be viewed as a key determinant of business conditions in global shipping. In this context, freight rate volatility may serve as a reasonable proxy for the industry’s core business risk. Notably, freight rates reveal considerable volatility clustering, i.e. we observe periods of high and low freight rate volatility, respectively. Given that periods of high (low) freight rate volatility are characterized by high (low) levels of investor uncertainty about fu-
ture earnings of shipping companies, we expect beta to be higher (lower) during such periods. In other words, freight rate volatility may reflect a cycle of industry business risk that might impact systematic risk in shipping stocks. For that reason, we rely on freight rate volatility to proxy for industry-related risks. Using the Clarksea index (CSI) as a proxy for the average charter rate over all shipping segments, we calculate the freight rate volatility in a given year as the twelve months rolling standard deviation of monthly index returns. Data on the BDI is obtained from Clarkon’s Shipping Intelligence Network.

To isolate a potential industry cycle effect in systematic risk from overall economy effects, the remaining factors control for further global macroeconomic sources of risk that affect investor uncertainty about future corporate income streams. To avoid multicollinearity issues, the set of global macro factors has been limited to the four variables stated above. Specifically, we use trend deviations from growth in total OECD industrial production to proxy for the global business cycle, the annual OECD inflation rate to control for investor uncertainty regarding expectations about the future value of money, the adequate discount rate and the present value of future cash flows, the credit spread as an indicator of global corporate financing risk (defined as the return differential between long-term BAA-rated and long-term AAA-rated corporate bonds), and the volatility of the USD-to-major-currencies exchange rate that reflects uncertainty about the value of earned income streams in local currency as explanatory variables in our systematic risk model. Data on industrial production and inflation is obtained from the OECD database, credit spread data is from the Federal Reserve’s Board of Governors database, and the exchange rate of USD against major currencies is from Thomson Financial Datastream.

### A.3 Institutional factors

The literature so far has directed attention solely to firm-specific and in parts to macroeconomic determinants of systematic risk. However, there may be arguments that systematic risk levels vary across different institutional environments. The ‘law and finance’ literature starting with La Porta et al. (1998) provides evidence for substantially different quality standards of legal systems around the world. Most relevant for the present study, legal protection guaranteed to investors is found to be rather limited in most countries, with common law coun-
tries providing higher investor protection than countries with a legal system originating in the civil law tradition. From an investor perspective, weak legal protection of financial claims against third parties constitutes investment risk that increases the variance of expected investment returns. Given that investors are not able to perfectly hedge against legal risks, they will call higher expected returns for being exposed to this additional risk factor. In other words, legal risk is systematic under this assumption.

The literature provides different measures of legal system quality and legal enforcement standards. In our analysis of systematic risk, we explicitly control for creditor and shareholder rights levels in the companies’ country of listing since these two factors are presumably the most important to corporate shareholders. Under the ceteris paribus condition, we argue that companies listed in countries with low shareholder rights are expected to exhibit higher levels of systematic risk than those listed in countries with strong shareholder rights. On the other hand, equity investors that invest in a country with strong creditor rights will face higher systematic risk than those investing in low creditor rights regimes. Paying attention to the notion that risk levels may also be driven by other institutional factors, we further add a control for the financial system in place that attempts to cover potentially omitted variables. The variable is designed to be equal to one for market-based financial systems and zero otherwise. To proxy for creditor rights and shareholder rights, we rely on the index measures provided by La Porta et al. (1998). Index values for the creditor rights index range from zero (weak creditor rights) to four (strong creditor rights). The shareholder rights index is defined on a scale from zero (weak shareholder rights) to five (strong shareholder rights). We use dummy variables marking countries with high legal standards to analyze the impact of both factors. Specifically, countries with creditor rights index values of 3 and 4 are defined as countries with strong creditor rights. In a similar manner, countries with shareholder index values of 4 and 5 are classified as having strong shareholder rights.

B. Empirical results

We use the defined systematic risk model to analyze the real determinants of beta. Coefficient estimates are obtained using firm-year panel regressions including segment-fixed effects. Regressions are run separately for each set of risk determinants (i.e. firm-specific, mac-
roeconomic, and institutional factors) and the full systematic risk model. In order to ease interpretation of the regression coefficients, we provide standardized regressions coefficients (except for the binary factors). Firms are required to provide non-missing data on all firm-specific variables to be included in the initial regression sample. The respective sample period is restricted to the years 1990 through 2013 due to limited data availability in the years prior to 1990. We end up with 1,363 firm-year observations. Table VI presents the empirical results.

[Insert Table VI here]

From Column (1), we recognize a statistically and economically significant impact of all firm-level factors. In line with theoretical expectations and prior empirical findings, operating and financial leverage constitute supplemental sources of corporate systematic risk, both revealing a positive relation with estimated market betas. Further, firms relying on large proportions of current assets and those having high payout ratios exhibit lower market risk on average while companies with high growth opportunities or a high default risk are exposed to higher levels of systematic risk. Column (2) presents coefficient estimates for the set of macroeconomic factors. Results reveal that both industry-specific risk characteristics (freight rate volatility) and the business cycle (industrial production growth) seem to drive observed beta risk in the time-series dimension. We observe higher levels of systematic risk during years of high freight rate volatility and through economic downturns with both coefficients being highly statistically significant. These findings are completely in line with theoretical expectations and have not been documented in the existing literature. Additionally, economy-wide refinancing risks as measured by the credit spread influence corporate risk levels. The coefficient estimate indicates higher beta values during times of high credit spreads. Inflation rates and the USD exchange rate are of minor importance.

Adding the set of institutional factors leaves us with the full systematic risk model. Single factor set evidence from Column (3) suggests that creditor rights indeed affect the systematic risk of a company. We find a significantly positive relation between creditor right and beta. This result supports the conjecture that strong creditor rights increase the investment risk of the individual equity investors and lead to higher risk levels in the cross-section. Though
have the expected signs, shareholder rights and the financial system factor do not have any significant impact.

All described effects remain unchanged in the full model. However, some of the factors exhibit a decrease in statistical significance. Most noteworthy, the coefficient estimate on default risk drops substantially, when we control for global economy and industry-related factors suggesting that default risk in fact seems to have a strong macroeconomic component. Overall, the full model results reveal that six factors seem to be of major importance in determining observed beta values, all being highly statistically significant. Still in line with expectations, operating leverage, financial leverage and corporate growth opportunities substantially influence systematic risk on the firm-level while industry conditions and the business cycle constitute aggregate drivers of beta over time. Although not covered in the literature so far, creditor rights have considerable impact on systematic risk levels.

C. In-sample predictions of systematic risk behavior

Regression results so far reveal that our systematic risk model provides reasonable links between expected real determinants of systematic risk and estimated betas. To develop a deeper understanding of the models explanatory power, this section analyzes in-sample predictions of systematic risk levels. We use the full model specification to obtain linear predictions of beta values in a given firm-year.

Figure III presents average estimated and predicted beta series over the regression sample period from 1990 through 2013. In a first step, Panel A compares estimated and predicted risk levels. In a subsequent step, we further split beta predictions into a firm-specific, an industry-related, and a macroeconomic component and compute predicted time-series for each set of factors based on the full model coefficient estimates. In order to investigate the single series’ contribution to the overall variation in predicted systematic risk, Panel B plots these conditional beta series and the full model predictions in terms of deviations from individual series means.

[Insert Figure III here]
Panel A reveals that the model performs quite well in predicting the cyclical behavior of estimated systematic risk. However, we recognize that the model fit is more accurate in the years from 2005 onwards while predicted betas do less precisely reflect the low systematic risk levels during the period 1995 through 2002. It is indeed surprising to some extent that model predictions exhibit a higher fit during the turbulent times of our sample period but notably peak values are not captured accurately in general, both during low and high beta periods, respectively. On the one hand, this could suggest the existence of an omitted time-related factor. However, the extreme beta periods have been characterized by extraordinary good/bad business conditions for the industry. Having this in mind, one may argue on the other hand that a constant coefficient model in general will not be able to capture such extreme values by construction. Obviously, this argument would be in favor of time-varying factor sensitivities but this is an issue not in the scope of the present study and has to be direct to future research.

The focus in Panel B is on pure predicted variability of beta and abstracts from individual time-series means to isolate the explanatory power of the different factor sets. The figure shows demeaned beta estimates and predictions for the full model as well as for the three subsets of explanatory factors. Results reveal that the downturn in predicted beta during the period from 1995 to 2002 may be attributed equally to firm-specific, macroeconomic, and industry-related effects. Similar patterns are observed for the final two sample years. Above average betas in the early years of the sample period seem to attributable to an increase in firm-specific and economy-wide risks. In contrast, the sharp increase in systematic risk levels from the beginning of the industry crisis in 2007 onwards is mainly based on industry conditions and global economy effects. This suggests that the observed risk cycle of shipping companies indeed reflects variations in industry-related and global economy risks, rather than an increase in the business risk specific to the operations of the average firm.

Overall, these results provide the first empirical evidence for a significant impact of industry-specific conditions on the beta of the individual firm. Accounting for both cross-sectional and time-series variation in estimated betas and controlling for global macroeconomic effects and the institutional environment a company operates in, we could further confirm that firm-specific real determinants substantially affect corporate risk levels. These findings are in line
with the theoretical literature and extend evidence by prior empirical studies based on cross-sectional analyses.

VI. Conclusions

This paper analyzes the industry impact on individual systematic risk levels. Using a sample of 150 globally-listed shipping companies over the period from 1973 through 2014, we first provide empirical evidence that estimated CAPM betas exhibit strong cross-sectional heterogeneity but basically reflect perceived industry risk characteristic in terms of their overall levels. Different estimation techniques are applied to obtain estimates for the market beta of the single firm. Estimated risk levels differ slightly across models, but we do not find significant differences in beta attributable to estimation methodology.

Inspired by prior studies that investigate fluctuations in market betas, we also examine the variability of beta through time. Using Kalman filtering and an MGRACH model we obtain monthly conditional estimates of beta. Although we observe strong intra-industry heterogeneity of risk levels across the individual firms, the time-series analysis of beta reveals a considerable industry cycle of risk which is consistent over the different industry segments including bulk, container, and tanker shipping and is also found for diversified shipping companies and different from the systematic risk behavior of the average industrial firm.

In subsequent analyses, we further investigate the real determinants of systematic risk levels in the industry. Our results indicate that firm-specific and institutional variables as well as macroeconomic and industry-related factors play an important role in determining beta. Specifically, the degree of operating leverage, financial leverage and corporate growth opportunities drive systematic risk levels in the cross-section of firms while industry risk and global economy effects account for major parts of the variation of beta through time. Not unexpected for a highly debt-financed industry, risk levels are generally higher in countries with strong creditor rights.

Our results support the view that market betas reflect underlying business risks of a company. Presented panel regression results provide first indication that drivers of systematic risk levels are of different dimensions, with macroeconomic and industry effects seeming to play a ma-
ajor role. However, findings in this study are based on a single industry. It is important in future work to figure out if risk cycles exist also in other sectors of the economy and if yes to which extent they differ across industries.
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Tables

**Table I**

**Summary Statistic of Stock Returns**

This table provides summary statistics of monthly stock returns for our sample of shipping companies. Statistics include the number of observations (N), the mean, the standard deviation (SD), the median, the 25th and 75th percentile, as well as the minimum (Min) and the maximum (Max) value of monthly stock returns for each operating segment. The sample consists of 150 listed shipping companies. The sample period is January 1973 through August 2014. For comparison reasons, the table further reports the return characteristics of the MSCI World index, the Fama-French factor portfolios for size and book-to-market, and the risk-free asset over the sample period.

<table>
<thead>
<tr>
<th>Segment</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Median</th>
<th>25th</th>
<th>75th</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>5,315</td>
<td>-0.005</td>
<td>0.175</td>
<td>0.000</td>
<td>-0.081</td>
<td>0.072</td>
<td>-0.653</td>
<td>0.575</td>
</tr>
<tr>
<td>Container</td>
<td>3,442</td>
<td>-0.002</td>
<td>0.149</td>
<td>0.000</td>
<td>-0.071</td>
<td>0.070</td>
<td>-0.511</td>
<td>0.472</td>
</tr>
<tr>
<td>Tanker</td>
<td>5,726</td>
<td>-0.007</td>
<td>0.146</td>
<td>0.000</td>
<td>-0.070</td>
<td>0.066</td>
<td>-0.548</td>
<td>0.424</td>
</tr>
<tr>
<td>Diversified</td>
<td>14,531</td>
<td>0.001</td>
<td>0.137</td>
<td>0.000</td>
<td>-0.067</td>
<td>0.069</td>
<td>-0.440</td>
<td>0.442</td>
</tr>
<tr>
<td>Total</td>
<td>29,014</td>
<td>-0.002</td>
<td>0.148</td>
<td>0.000</td>
<td>-0.070</td>
<td>0.069</td>
<td>-0.653</td>
<td>0.575</td>
</tr>
</tbody>
</table>

**Benchmarks**

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Median</th>
<th>25th</th>
<th>75th</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSCI World Index</td>
<td>500</td>
<td>0.008</td>
<td>0.044</td>
<td>0.012</td>
<td>-0.016</td>
<td>0.034</td>
<td>-0.210</td>
<td>0.137</td>
</tr>
<tr>
<td>SMB portfolio</td>
<td>500</td>
<td>0.002</td>
<td>0.031</td>
<td>0.001</td>
<td>-0.015</td>
<td>0.020</td>
<td>-0.164</td>
<td>0.220</td>
</tr>
<tr>
<td>HML portfolio</td>
<td>500</td>
<td>0.004</td>
<td>0.030</td>
<td>0.003</td>
<td>-0.012</td>
<td>0.018</td>
<td>-0.126</td>
<td>0.139</td>
</tr>
<tr>
<td>Risk-free rate</td>
<td>500</td>
<td>0.004</td>
<td>0.003</td>
<td>0.004</td>
<td>0.002</td>
<td>0.006</td>
<td>0.000</td>
<td>0.014</td>
</tr>
</tbody>
</table>
The table reports market beta estimates for the full sample period. Firm-specific estimates are based on the entire available firm history of stock returns. Results include CAPM-based (CAPM) and 3-factor model-based (FF3) estimates as well as Dimson (DIM) and Scholes-Williams (SW) betas and corresponding standard deviations of beta (SD) for each operating segment. Additionally, we report average estimates for each market beta decile with corresponding standard deviations.

<table>
<thead>
<tr>
<th>Segment</th>
<th>$\beta^{\text{CAPM}}$</th>
<th>SD</th>
<th>$\beta^{\text{FF}}$</th>
<th>SD</th>
<th>$\beta^{\text{SW}}$</th>
<th>SD</th>
<th>$\beta^{\text{Dimson}}$</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>1.254</td>
<td>0.773</td>
<td>1.304</td>
<td>0.772</td>
<td>1.044</td>
<td>0.878</td>
<td>1.207</td>
<td>1.327</td>
</tr>
<tr>
<td>Container</td>
<td>1.012</td>
<td>0.466</td>
<td>1.015</td>
<td>0.445</td>
<td>0.894</td>
<td>0.401</td>
<td>1.033</td>
<td>0.891</td>
</tr>
<tr>
<td>Tanker</td>
<td>0.950</td>
<td>0.445</td>
<td>0.975</td>
<td>0.409</td>
<td>0.823</td>
<td>0.486</td>
<td>1.282</td>
<td>1.851</td>
</tr>
<tr>
<td>Diversified</td>
<td>0.987</td>
<td>0.503</td>
<td>1.008</td>
<td>0.529</td>
<td>0.794</td>
<td>0.509</td>
<td>0.995</td>
<td>0.526</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Market Beta Deciles:</th>
<th>$\beta^{\text{CAPM}}$</th>
<th>SD</th>
<th>$\beta^{\text{FF}}$</th>
<th>SD</th>
<th>$\beta^{\text{SW}}$</th>
<th>SD</th>
<th>$\beta^{\text{Dimson}}$</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Market Beta Decile</td>
<td>0.158</td>
<td>0.155</td>
<td>0.143</td>
<td>0.208</td>
<td>-0.092</td>
<td>0.263</td>
<td>-0.888</td>
<td>0.984</td>
</tr>
<tr>
<td></td>
<td>0.489</td>
<td>0.078</td>
<td>0.544</td>
<td>0.072</td>
<td>0.317</td>
<td>0.076</td>
<td>0.356</td>
<td>0.136</td>
</tr>
<tr>
<td></td>
<td>0.673</td>
<td>0.039</td>
<td>0.716</td>
<td>0.042</td>
<td>0.520</td>
<td>0.045</td>
<td>0.656</td>
<td>0.101</td>
</tr>
<tr>
<td></td>
<td>0.808</td>
<td>0.048</td>
<td>0.858</td>
<td>0.045</td>
<td>0.666</td>
<td>0.043</td>
<td>0.891</td>
<td>0.053</td>
</tr>
<tr>
<td></td>
<td>0.932</td>
<td>0.022</td>
<td>0.949</td>
<td>0.019</td>
<td>0.770</td>
<td>0.020</td>
<td>1.019</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>1.014</td>
<td>0.038</td>
<td>1.051</td>
<td>0.023</td>
<td>0.850</td>
<td>0.027</td>
<td>1.159</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td>1.166</td>
<td>0.057</td>
<td>1.190</td>
<td>0.044</td>
<td>0.986</td>
<td>0.064</td>
<td>1.309</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td>1.353</td>
<td>0.043</td>
<td>1.372</td>
<td>0.059</td>
<td>1.179</td>
<td>0.038</td>
<td>1.517</td>
<td>0.082</td>
</tr>
<tr>
<td></td>
<td>1.644</td>
<td>0.096</td>
<td>1.605</td>
<td>0.085</td>
<td>1.432</td>
<td>0.099</td>
<td>1.857</td>
<td>0.099</td>
</tr>
<tr>
<td>High Market Beta Decile</td>
<td>2.164</td>
<td>0.309</td>
<td>2.232</td>
<td>0.290</td>
<td>2.057</td>
<td>0.476</td>
<td>3.274</td>
<td>1.719</td>
</tr>
<tr>
<td>Total</td>
<td>1.040</td>
<td>0.564</td>
<td>1.066</td>
<td>0.568</td>
<td>0.869</td>
<td>0.597</td>
<td>1.115</td>
<td>1.187</td>
</tr>
</tbody>
</table>
Table III

Summary of Dynamic Beta Estimates

The table reports average market beta estimates obtained from the dynamic beta estimation methods separately for each shipping segment and the overall sample. Additionally, we provide mean values for each market beta decile. Reported standard deviations refer to the distribution of monthly betas in the respective subgroups. Kalman filter and Kalman smoother values exclude the initial 12 observations for each firm to account for the initialization period of the algorithm.

<table>
<thead>
<tr>
<th>Segment</th>
<th>β^Filter</th>
<th>SD</th>
<th>β^Smother</th>
<th>SD</th>
<th>β^Rolling</th>
<th>SD</th>
<th>β^MGARCH</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>1.099</td>
<td>0.610</td>
<td>1.212</td>
<td>0.739</td>
<td>1.241</td>
<td>0.782</td>
<td>1.359</td>
<td>0.861</td>
</tr>
<tr>
<td>Container</td>
<td>1.014</td>
<td>0.436</td>
<td>1.008</td>
<td>0.465</td>
<td>1.042</td>
<td>0.495</td>
<td>1.250</td>
<td>0.881</td>
</tr>
<tr>
<td>Tanker</td>
<td>0.932</td>
<td>0.469</td>
<td>0.976</td>
<td>0.461</td>
<td>0.958</td>
<td>0.480</td>
<td>1.350</td>
<td>1.261</td>
</tr>
<tr>
<td>Diversified</td>
<td>0.959</td>
<td>0.527</td>
<td>0.992</td>
<td>0.522</td>
<td>0.996</td>
<td>0.533</td>
<td>1.029</td>
<td>0.538</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Market Beta Deciles:</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Market Beta Decile</td>
<td>0.194</td>
<td>0.086</td>
<td>0.183</td>
<td>0.144</td>
<td>0.140</td>
<td>0.172</td>
<td>0.183</td>
<td>0.195</td>
</tr>
<tr>
<td></td>
<td>0.441</td>
<td>0.060</td>
<td>0.478</td>
<td>0.070</td>
<td>0.473</td>
<td>0.072</td>
<td>0.557</td>
<td>0.064</td>
</tr>
<tr>
<td></td>
<td>0.590</td>
<td>0.056</td>
<td>0.701</td>
<td>0.046</td>
<td>0.673</td>
<td>0.048</td>
<td>0.755</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>0.777</td>
<td>0.044</td>
<td>0.824</td>
<td>0.025</td>
<td>0.800</td>
<td>0.050</td>
<td>0.881</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>0.908</td>
<td>0.034</td>
<td>0.924</td>
<td>0.027</td>
<td>0.944</td>
<td>0.027</td>
<td>1.003</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>1.014</td>
<td>0.027</td>
<td>1.013</td>
<td>0.021</td>
<td>1.029</td>
<td>0.037</td>
<td>1.151</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>1.098</td>
<td>0.028</td>
<td>1.133</td>
<td>0.042</td>
<td>1.136</td>
<td>0.035</td>
<td>1.270</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td>1.300</td>
<td>0.077</td>
<td>1.316</td>
<td>0.051</td>
<td>1.348</td>
<td>0.090</td>
<td>1.492</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td>1.568</td>
<td>0.082</td>
<td>1.632</td>
<td>0.138</td>
<td>1.709</td>
<td>0.105</td>
<td>1.821</td>
<td>0.131</td>
</tr>
<tr>
<td>High Market Beta Decile</td>
<td>2.009</td>
<td>0.213</td>
<td>2.180</td>
<td>0.335</td>
<td>2.213</td>
<td>0.302</td>
<td>2.956</td>
<td>1.543</td>
</tr>
<tr>
<td>Total</td>
<td>0.990</td>
<td>0.522</td>
<td>1.038</td>
<td>0.560</td>
<td>1.047</td>
<td>0.585</td>
<td>1.207</td>
<td>0.877</td>
</tr>
</tbody>
</table>
Table IV
Overview of In-Sample Forecast Errors

The table reports estimated forecasting errors for all static and dynamic beta estimation methods separately for each shipping segment and the overall sample. We report mean absolute errors (MAE) and means squared errors (MSE). Kalman filter and Kalman smoother values exclude the initial 12 observations for each firm to account for the initialization period of the algorithm.

<table>
<thead>
<tr>
<th>Segment</th>
<th>( \beta^{\text{CAPM}} )</th>
<th>( \beta^{\text{FF}} )</th>
<th>( \beta^{\text{SW}} )</th>
<th>Dimson</th>
<th>( \beta^{\text{Filter}} )</th>
<th>Smoother</th>
<th>( \beta^{\text{Rolling}} )</th>
<th>MGARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>0.1100</td>
<td>0.1094</td>
<td>0.1102</td>
<td>0.1122</td>
<td>0.1046</td>
<td>0.1055</td>
<td>0.1110</td>
<td>0.1117</td>
</tr>
<tr>
<td>Container</td>
<td>0.0948</td>
<td>0.0944</td>
<td>0.0957</td>
<td>0.0960</td>
<td>0.0905</td>
<td>0.0915</td>
<td>0.0944</td>
<td>0.0964</td>
</tr>
<tr>
<td>Tanker</td>
<td>0.0941</td>
<td>0.0931</td>
<td>0.0944</td>
<td>0.0979</td>
<td>0.0900</td>
<td>0.0912</td>
<td>0.0941</td>
<td>0.0954</td>
</tr>
<tr>
<td>Diversified</td>
<td>0.0886</td>
<td>0.0877</td>
<td>0.0889</td>
<td>0.0896</td>
<td>0.0838</td>
<td>0.0848</td>
<td>0.0880</td>
<td>0.0892</td>
</tr>
<tr>
<td>Total</td>
<td>0.0939</td>
<td>0.0931</td>
<td>0.0942</td>
<td>0.0956</td>
<td>0.0892</td>
<td>0.0902</td>
<td>0.0937</td>
<td>0.0949</td>
</tr>
</tbody>
</table>

Panel B: Mean squared forecast errors (MSE)

<table>
<thead>
<tr>
<th>Segment</th>
<th>( \beta^{\text{CAPM}} )</th>
<th>( \beta^{\text{FF}} )</th>
<th>( \beta^{\text{SW}} )</th>
<th>Dimson</th>
<th>( \beta^{\text{Filter}} )</th>
<th>Smoother</th>
<th>( \beta^{\text{Rolling}} )</th>
<th>MGARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulk</td>
<td>0.0252</td>
<td>0.0249</td>
<td>0.0254</td>
<td>0.0259</td>
<td>0.0227</td>
<td>0.0234</td>
<td>0.0254</td>
<td>0.0263</td>
</tr>
<tr>
<td>Container</td>
<td>0.0180</td>
<td>0.0179</td>
<td>0.0182</td>
<td>0.0184</td>
<td>0.0164</td>
<td>0.0168</td>
<td>0.0178</td>
<td>0.0189</td>
</tr>
<tr>
<td>Tanker</td>
<td>0.0187</td>
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<td>0.0189</td>
<td>0.0198</td>
<td>0.0171</td>
<td>0.0176</td>
<td>0.0189</td>
<td>0.0194</td>
</tr>
<tr>
<td>Diversified</td>
<td>0.0153</td>
<td>0.0151</td>
<td>0.0155</td>
<td>0.0156</td>
<td>0.0138</td>
<td>0.0142</td>
<td>0.0151</td>
<td>0.0157</td>
</tr>
<tr>
<td>Total</td>
<td>0.0179</td>
<td>0.0176</td>
<td>0.0181</td>
<td>0.0184</td>
<td>0.0162</td>
<td>0.0166</td>
<td>0.0178</td>
<td>0.0185</td>
</tr>
</tbody>
</table>
The table reports average annual Kalman filter market beta estimates over time separately for each shipping segment and the overall sample. The sample period is limited to the years 1990 through 2014 due to limited observations in the cross-section prior to 1990.

<table>
<thead>
<tr>
<th>Year</th>
<th>Bulker Filter</th>
<th>Bulker SD</th>
<th>Container Filter</th>
<th>Container SD</th>
<th>Tanker Filter</th>
<th>Tanker SD</th>
<th>Diversified Filter</th>
<th>Diversified SD</th>
<th>Total Filter</th>
<th>Total SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0.818</td>
<td>0.788</td>
<td>1.204</td>
<td>0.279</td>
<td>0.927</td>
<td>0.307</td>
<td>1.032</td>
<td>0.893</td>
<td>1.000</td>
<td>0.734</td>
</tr>
<tr>
<td>1991</td>
<td>0.708</td>
<td>0.896</td>
<td>1.135</td>
<td>0.209</td>
<td>0.802</td>
<td>0.404</td>
<td>0.985</td>
<td>0.935</td>
<td>0.925</td>
<td>0.803</td>
</tr>
<tr>
<td>1992</td>
<td>0.753</td>
<td>0.733</td>
<td>1.038</td>
<td>0.210</td>
<td>0.807</td>
<td>0.368</td>
<td>0.924</td>
<td>0.935</td>
<td>0.883</td>
<td>0.783</td>
</tr>
<tr>
<td>1993</td>
<td>0.721</td>
<td>0.635</td>
<td>1.161</td>
<td>0.436</td>
<td>0.792</td>
<td>0.317</td>
<td>0.778</td>
<td>0.889</td>
<td>0.802</td>
<td>0.741</td>
</tr>
<tr>
<td>1994</td>
<td>0.751</td>
<td>0.520</td>
<td>1.091</td>
<td>0.441</td>
<td>0.818</td>
<td>0.296</td>
<td>0.700</td>
<td>0.751</td>
<td>0.759</td>
<td>0.630</td>
</tr>
<tr>
<td>1995</td>
<td>0.651</td>
<td>0.486</td>
<td>0.869</td>
<td>0.407</td>
<td>0.729</td>
<td>0.352</td>
<td>0.671</td>
<td>0.643</td>
<td>0.695</td>
<td>0.544</td>
</tr>
<tr>
<td>1996</td>
<td>0.580</td>
<td>0.484</td>
<td>0.646</td>
<td>0.501</td>
<td>0.738</td>
<td>0.367</td>
<td>0.630</td>
<td>0.570</td>
<td>0.644</td>
<td>0.508</td>
</tr>
<tr>
<td>1997</td>
<td>0.527</td>
<td>0.453</td>
<td>0.507</td>
<td>0.414</td>
<td>0.704</td>
<td>0.410</td>
<td>0.576</td>
<td>0.520</td>
<td>0.583</td>
<td>0.473</td>
</tr>
<tr>
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Table VI
Determinants of Beta

The table reports regression results for market beta determinants. Monthly Kalman filter estimated betas are and annual accounting data are matched on a fiscal year-end basis. Market beta is modeled as a function of firm-specific, macroeconomic, industry-related, and institutional factors (as described in Section V). We report standardized regression coefficients for all non-binary variables. All regression specifications include segment-fixed effects. Standard errors control for clustering at the firm level. Respective p-values are given in parentheses. ***, ** and * denote statistical significance at the 1%, the 5% and the 10% level, respectively.

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Figures

Figure I. Overview of beta estimates for A.P. Møller - Mærsk A/S. The figure presents the time-series estimates for ‘A.P. Møller - Mærsk A/S’ over the full sample period from January 1973 through August 2014. The time-series of rolling window estimates starts with a time-lag of 5 years due to the estimation window of 60 months. We further dropped the first 12 observations of the Kalman filter and Kalman smoother estimates to account for initialization of the filter algorithm.
Figure II. Beta estimates by segment over time. The figure shows average annual market beta estimates over time. For comparison reasons, we further report the average annual beta of all S&P 500 firms as a benchmark. The sample period is limited to the years 1990 through 2014 due to limited observations in the cross-section prior to 1990.
Panel A: Predicted systematic risk levels

Panel B: Variation in predicted systematic risk levels

Figure III. In-sample predictions of systematic risk behavior. The figure shows the estimated and predicted behavior of systematic risk. Estimated betas are those obtained via Kalman filtering. Linear predictions of beta are drawn from the full specification of the systematic risk model. Panel A presents estimated and predicted systematic risk levels in terms of annual mean values. Panel B describes beta variation in deviations from individual series means. Factor set-based series in Panel B include beta predictions according to estimated coefficients from full model specifications for the different bundles of explanatory variables. According to the regression sample the presented sample period is limited to the years 1990 through 2013 to ensure that mean values are based on a sufficient number of observations.