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HFRC Working Paper Series No.9 – December 2015

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Systematic risk behavior in cyclical industries: The case of shipping

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This version: December 2015

Abstract

This study explores macroeconomic and industry-level effects on corporate systematic risk (or beta) for the international shipping industry. We document the extent to which stock market betas fluctuate over time in this asset-intensive and cyclical industry. Moreover, we analyze the fundamental determinants of systematic risk. We find evidence for high levels of systematic risk in shipping stocks, which match the fundamental risk characteristics of the industry (such as high operational risk and high financial as well as operating leverage). Shipping firms exhibit very distinct industry-specific beta dynamics compared to firms from benchmark sectors or the average firm in the S&P 500 index. Changes in both economic conditions and industry-specific risk factors explain large proportions of beta variation in the cross-section of firms and over time.

Keywords: Maritime financial management, time-varying systematic risk, real determinants
JEL: G10, G30

1 Introduction

In modern finance, betas, or sensitivities of asset returns to underlying sources of risk, are the central concept to model and control an asset's systematic risks. The stock market beta is a major determinant of expected stock returns in both the CAPM framework (Sharpe (1964), Lintner (1965), Mossin (1966)) and its descendents, such as the intertemporal CAPM (ICAPM; Merton (1973)) and multi-factor (beta pricing) models (Ross (1976), Fama and French (1993, 1995)). It is widely used by both academics and practitioners to compute a firm's cost of equity, assess single investment projects,

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and evaluate the entire company. Given the importance of betas for investors and corporate managers, it is crucial to examine empirically how they are determined. In fact, empirical evidence suggests that systematic risk and its determinants may differ substantially across industries (Fama and French (1997)). Contributing to the empirical literature on industry-specific systematic risk levels, we analyze the international shipping sector as a specific case of a cyclical and risk-loaded industry.

Although the shipping industry is a key sector in the international economy, it has hardly been studied in an asset pricing context.[1] However, especially in the light of the industry's recent financing problems a fundamental understanding of its stock market risk seems of particular relevance. The ongoing shipping crisis with its low forecasted future returns (Greenwood and Hanson (2014)) and the Basel III equity capital regulation for banks have led to a lack of available bank financing for new vessels.[2] A consequence of the lower levels of available bank credit is that more and more shipping firms have approached the international capital markets during recent years. Therefore, knowledge about both the level and the drivers of systematic risk is of eminent importance for corporate financial managers. Specifically, they are needed to estimate the cost of equity capital, which are a key input parameter to evaluate and identify profitable investment decisions. In this study, we address both issues. First, we analyze the cross-sectional and time-series dynamics of systematic risk levels in the shipping industry based on a comprehensive sample of internationally-listed shipping companies. Second, we provide a detailed analysis of the industry's fundamental market risk determinants. Our results show that shipping companies feature beta characteristics and systematic risk levels which are substantially different from other industries, both in terms of its time-series dynamics and its underlying factors.

According to standard theory, the stock market beta reflects a firm's incremental business risk. The CAPM assumes that investors are well-diversified, and thus the only risk an investor perceives in an investment is the risk that cannot be diversified (i.e., market risk or systematic risk). The stock market beta is the model's measure of systematic risk contribution.[3] In particular, the CAPM proposes that investors only care about stock market betas because these measure the risk components which investors who hold a fully diversified portfolio (or the market portfolio) cannot diversify. Early empirical studies emphasize that accounting measures of risk related to uncertainty in firms' cash flows are positively correlated with their systematic risk levels (Beaver et al. (1970), Logue and Merville (1972), Melicher (1974)).[4] More recent work by Campbell and Mei (1993) supports the

[1] A notable exception is the recent study by Panayides et al. (2013), who estimate liquidity risk premiums for US water transportation stocks. They show that illiquidity risk is priced in the water transportation sector beyond the Fama and French (1993) and market-wide illiquidity risk factors, indicating the existence of a risk premium and higher average returns for stocks with greater illiquidity measures.

[2] Some shipping banks even left the market, and the remaining ones have become very selective on their core clients. Commerzbank, Germany's second largest banking house, is a prominent example. For many years, it ranked second in terms of the volume of outstanding shipping loans among German lenders. The bank announced to pull out of ship finance „as part of a strategic review promoted by the financial crisis and tougher capital requirements under the Basel III rulebook"(Financial Times (2012)).

[3] An investment's cost of equity is lower when it offers diversification benefits for an investor holding the market portfolio, i.e., it requires less reward for less risk contribution. The contribution to the overall portfolio risk is the market beta of a firm — a measure of the firm's toxicity. A stock that decreases in value when the market decreases in value, and increases when the market increases, has a positive beta - it is toxic, and investors avoid it. In contrast, a stock with a low beta helps an investor who holds the market portfolio to reduce the overall investment risk.

[4] Nickel and Rodriguez (2002) provide a review on the accounting relationship between risk and return.

idea that betas are determined by shocks to their cash flows (and shocks to their discount rates). Campbell (1993, 1996) and Campbell and Vuolteenaho (2004) propose a version of the ICAPM, in which investors care more about cash flow-driven movements than about temporary discount rate-driven movements in the aggregate stock market. In their model, the required return on a stock is not determined by its overall beta, but by two separate betas, one with permanent cash flow shocks to the market and another with temporary shocks to market discount rates.[5] While these studies rely on cross-sectional analyses or consider only some arbitrarily chosen sub-periods of time, their results are consistent with the view that varying levels of cash flow risk are reflected in firms' stock market betas. However, they cannot provide direct evidence on the behavior of systematic risk over time, and are also not able to identify factors that drive time variation in stock market betas.

Focusing on the time-dimension of beta, Bos and Newbold (1984) argue that both changes in microeconomic factors (the business risk specific to a firm's operations) and macroeconomic conditions (the changes in global economic conditions or industry-related factors) affect systematic risk levels. This conjecture is closely related to recent theoretical work by Gomes et al. (2003) and the empirical asset pricing literature on time-varying betas (Bollerslev et al. (1988), Jagannathan and Wang (1996), Lettau and Ludvigson (2001b), Lewellen and Nagel (2006)). Market betas tend to be higher during bad economic regimes, and lower during good economic states. Such business cycle effects on systematic risk are expected to be stronger if a firm operates in sectors of the economy that exhibit a higher exposure to fluctuations in global business conditions, hence providing an explanation for industry-specific difference in systematic risk dynamics. Isolating the cash flow impact on betas, i.e., the beta effects associated with changes in expectations about future cash flows, Campbell and Mei (1993) find that cash flow induced risk in betas is substantially higher for cyclical industries. This argument for industry-dependent macroeconomics effects on beta is further supported by Gomes et al. (2003). Their theoretical model predicts higher cross-sectional beta dispersion during weak economic conditions.

Shipping has always been a volatile business (Drobetz et al. (2012), Kalouptsidi (2014), Greenwood and Hanson (2014)). The demand for seaborne transport is a direct derivative of global trade and consequently industry cash flows in shipping are tightly linked to the business cycle. Moreover, the shipping industry exhibits high financial and operating leverage (Drobetz et al. (2013)). Given these fundamental business risks, asset pricing theory would suggest that shipping firms exhibit substantially time-variable and relatively high stock market betas compared to other industries. Focusing purely on the average systematic risk level in shipping stocks, however, existing studies report surprisingly low market betas. Empirical work that explores the level of systematic risk in the shipping industry include a series of studies by Kavussanos and Marcoulis (1997a,b, 1998, 2000a,b, 2005) and Kavussanos et al. (2003). These studies report betas close to one for their samples of listed shipping companies. Drobetz et al. (2010) test multifactor models in a stochastic discount factor setup. They also document that shipping stocks exhibit remarkably low stock market betas. A caveat in all these studies is the OLS-based evaluation of market betas. Constant beta estimates can

[5] Campbell and Vuolteenaho (2004) call the first beta with respect to cash flow shocks 'bad beta', because investors demand a high risk premium to hold assets that covary with the market's cash flow news. The second beta with respect to discount rate shocks is called 'good beta'. Poor returns driven by increases in discount rates are partially compensated by improved prospects for future returns, thus investors remand a relatively low price of risk.

only provide a measure of the average level of market risk, which is clearly inappropriate if stock market betas are time-varying. First empirical evidence for a relatively small shipping sample by Gong et al. (2006) indicates that shipping stocks indeed involve time-varying systematic risk. The authors document different market beta estimates for the individual shipping stocks during different sub-periods. However, they provide neither support for a congruent behavior of market risk across different firms nor for common underlying risk determinants in the shipping industry.

Our empirical analyses are based on a comprehensive dataset of 150 globally-listed shipping companies over the time period from 1990 to 2013. Compared to prior industry studies, our sample allows for a detailed analysis of shipping firms' stock market betas both in the cross-section and in the time-series dimension. Using a conditional CAPM framework, we obtain time-varying estimates of monthly betas and analyze the changes in the levels of industry risk over time. Estimated stock market betas fluctuate considerably during the sample period. In particular, we find that the levels of systematic risk of shipping companies exhibit a strong industry cycle compared to a benchmark sector and the average S&P 500 company. Kalman filter-based estimates show that the average industry beta varies between 0.583 and 1.292 during the years of our sample period. The cycle patterns in beta risk are very similar over the different shipping segments. In fact, depending on the sample year, shipping companies are substantially more (less) risky than the overall stock market. As expected, the estimated betas peak during the recent shipping crisis from 2007 onwards, which has led to severe turbulences in the maritime sector. These results strongly suggest that controlling for time-variation in beta is crucial in the evaluation of corporate risk levels. Specifically, relying on constant OLS-based stock market beta and cost of equity estimates may lead to sub-optimal decisions in the capital budgeting process.

Further empirical analyses focus on the determinants of shipping betas. Based on the existing literature, we suggest that both macro- and microeconomic, but also industry-specific conditions will affect stock market betas. Using panel regression methodology including a set of firm-specific, macroeconomic, and industry-related variables to explain the observed levels of systematic risk, we analyze both the cross-sectional and the time variation in stock market betas. We analyze the relative influence of these factors and find that, in particular, macroeconomic and industry-related variables explain large proportions of beta fluctuations. Firm-specific characteristics play a role in determining the level of beta for each firm, but they are not important for explaining the strong time variation in stock market betas. In comparison with a benchmark sector, our results reveal that the systematic risk drivers in shipping are different from those in other industries. The findings are robust after controlling for industry-segment effects as well as the institutional environment a firm operates in. Overall, our findings suggest that the levels of systematic risk reflect the cyclical nature of the international shipping industry.

The remainder is structured as follows: Section 2 provides the theoretical framework. Section 2 describes the sample selection and reviews the data. Section 4 illustrates the behavior of systematic risk in shipping stocks over time. Section 5 analyzes the fundamental determinants and drivers of stock market risk in the shipping industry. Finally, Section 6 concludes and discusses implications for financial decision makers in the shipping industry.

2 The empirical framework

To model fluctuations in the systematic risk levels of shipping stocks, we refer to a conditional formulation of the CAPM. 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 return on the market portfolio. Equation (1) provides the time-varying parameter formulation of the empirical CAPM in its most stylized manner:

$$(r_{i,t} - r_{f,t}) = \alpha_{i,t} + \beta_{i,t}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return of the shipping stock at time t, $r_{m,t}$ is the return of the market portfolio, $r_{f,t}$ is the risk-free rate, and $\beta_{i,t}$ is the asset's non-diversifiable systematic risk in relation to the overall market risk at time t.

Modeling the time variation in beta is similarly conceivable in a multi-dimensional (beta pricing) model. We nevertheless decide to perform the following analyses on the theoretical basis of the CAPM since our primary interest is in the overall stock market beta rather than in other factor betas that account for different dimensions of systematic risk. Further, the CAPM is preferable from the econometric perspective as the most parsimonious model that minimizes the number of parameters to be estimated in the dynamic framework.[6]

To obtain time-varying monthly beta estimates, we use the Kalman filtering approach. This involves formulating the standard CAPM in a state-space framework, where the asset's exposure to the overall market is considered to be an unobserved state variable following some underlying stochastic process. For our purposes, we assume the stock market beta to evolve according to a random walk. In this simple setting, changes in beta are only expected if new information is available, i.e., $E[\Delta\beta_t|\psi_{t-1}] = 0$, with ψ 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:

$$(r_{i,t} - r_{f,t}) = \alpha_{i,t} + \beta_{i,t}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{2}$$

$$\alpha_{i,t} = \alpha_{i,t-1} + \upsilon_{i,t} \tag{3}$$

$$\beta_{i,t} = \beta_{i,t-1} + \eta_{i,t} \tag{4}$$

Following earlier work (Bollen and Whaley (2009), among others), we assume the error terms to be independent, homoscedastic, and serially uncorrelated:

$$\varepsilon_{i,t} \backsim MVN(0,P),\ \upsilon_{i,t} \backsim MVN(0,Q),\ \text{and}\ \eta_{i,t} \backsim MVN(0,K)$$

where P, Q, and K are covariance matrices. Departing from the initial state values, the Kalman filter provides recursive conditional estimates of the asset-specific state variables α and β for each time t up to T. The Kalman filter refers to estimates of $\beta_{i,t}$ based on information available up to time t.

[6] Untabulated robustness test reveal that CAPM-based and Fama and French (1993)-based stock market betas are very similar for our sample of shipping companies. We therefore hypothesize that omitting other risk factors does not bias our stock market beta estimates.

Following Harvey (1989), we initialize the Kalman filter using arbitrary values for the state variables α and β and the corresponding covariance matrices with large diagonal elements which reflect the uncertainty of the initial values.[7]

3 Data and descriptive statistics

Our empirical analysis of systematic risk in the shipping industry is based on an international sample of 150 listed shipping companies from 35 countries. Sample firms are selected based on the condition that they own and operate commercial freight ships. The underlying universe of shipping firms was identified using Thomson Datastream business descriptions as well as publicly available information from websites and annual reports. This information set is further used to categorize firms into different shipping segments. In particular, we sort the sample companies into four segments: 'Bulk' (33 firms), 'Container' (19 firms), 'Tanker' (36 firms; including LPG shipping), and 'Diversified' (62 firms), where 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 all our analyses. Our sampling procedure ensures that the sample only comprises shipping firms in the sense of freight shipping companies. We exclude shipyards and shipping companies involved in passenger shipping, or those operating drilling ships, supply vessels, and inland vessels since these firms are fundamentally different in the nature of their operations and arguably feature systematic risk characteristics different from the 'core' industry.

Monthly stock price data in US$ for all sample firms and monthly index values for the MSCI World stock market index (MSCI World) are obtained from Thomson Financial Datastream. Assuming globally integrated stock markets (Bekaert and Harvey (1995)), we compute continuously compounded (total) returns for each sample firm and use the MSCI World index as our proxy for the global market portfolio. Risk-free returns are approximated by the one-month T-bill rate from Ibbotson Associates.[8] To ensure robust estimation of market betas, we require firms to have at least 60 months (five 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 over the sample period from January 1973 to August 2014. Table 1 shows the distribution of firms and firm-year observations in our sample with respect to the firms' ISIN-issuing country and over time, respectively. In order to base or analyses on a sufficient number of firms in the cross-section, we restrict our final sample to the years 1990 through 2013.

[Insert Table 1 here]

[7] Results for repeated initializations with different values indicate that the series of states estimates is insensitive to the choice of the initial values.

[8] See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library`.

The firm-year panel applied in Section 5 is obtained by combining annual accounting data and monthly stock market data (including beta estimates) on a fiscal year-end basis. This procedure allows us to explain fiscal year-end systematic risk levels using fiscal year-end accounting fundamentals. Annual accounting information used to construct proxies for firm-specific risk characteristics is obtained from Standard & Poor's Compustat Global database. The final annual sample used in this section spans the period from 1990 through 2013 and includes 1,363 firm-year observations. More detailed information on the sample selection for the firm-year panel is provided in Sections 5.1 and 5.2.1 below.

Summary statistics for our monthly sample of shipping stock returns, the MSCI World, and the risk-free asset are provided in Table 2. Notably, shipping stocks feature specific return characteristics. Except for the diversified segment, average monthly shipping stock returns are slightly negative during our sample period. Compared to the MSCI, we observe a relatively high volatility of monthly stock returns in all shipping segments, as indicated by the standard deviation and the observed tail values (Min./Max.). Quartile values of monthly stock returns range from -8.1 percent (first quartile) to 7.2 percent (fourth quartile). Differences in the reported return characteristics compared to prior studies which document slightly positive average returns of shipping companies are attributable to the differences in the underlying sample periods. While these studies examine sample periods until 2006 at most, our sample provides a more comprehensive picture, also covering the crisis years of the industry from 2007 onwards.

[Insert Table 2 here]

4 Time-varying systematic risk levels

Low static beta estimates for cyclical industries may at least partly be the result of variation in stocks' true market exposure over time. Suppose, for example, a firm has a high beta (say 1.5) during one half of the sample period and a low beta (say 0.5) during the other. Market model estimates via OLS only reflect an average beta, which will be indistinguishable from that of the overall market, although the stock's true beta delineates completely different risk characteristics.

In this section, we provide evidence for a time-varying systematic risk component in shipping stock returns, which may also explain the finding of moderate market betas of shipping companies in prior studies.[9] By way on an example, Figure 1 depicts the time series estimates for A.P. Møller-Mærsk A/S, one of the firms in our sample that provides data over the full sample period from January 1973 to August 2014. We dropped the first 12 observations of the Kalman filter estimates to account for initialization of the filter algorithm. Obviously, there is considerable cyclicality in the beta series, peaking during the recent years, when the industry was hit by its most severe crisis in history. For comparison, we also show the static CAPM estimates. As expected, the static

[9] Another explanation for the low static betas of shipping stocks is related to the supply-side dynamics of shipping. In fact, supply of tonnage is effectively independent of the contemporaneous business cycle due to the delivery lead time of vessels. This lead-lag relationship implies that the freight market exhibits a relatively low correlation with other industries and the overall stock market. Therefore, while freight markets exhibit high volatility but modest correlation with the stock market, industry betas may seem 'surprisingly' low.

beta estimate closely resembles the average of the conditional time series and is slightly below unity.

[Insert Figure 1 here]

We next analyze fluctuations in Kalman filter betas in more detail. Figures 2 and 3 present a graphical illustration of average annual beta estimates for the years 1990 to 2013, separately for each shipping segment and the entire sample.[10] For comparison reason, we further include two benchmarks: (i) the average annual betas of all firms contained in the S&P 500 index during the sample period, and (ii) the average annual beta estimates of all manufacturing firms contained in the S&P 500.

[Insert Figures 2 and 3 here]

Notably, shipping beta exhibit considerable time variation; this holds for all segments and the full sample, and generalizes the intuition already suggested by the A.P. Møller-Mærsk A/S example in Figure 1. Stock market betas were relatively low in the early 1990s, and increased notably at the beginning of the 2000s. They peaked during the years from 2007 onwards, when the industry was hit by the most severe crisis in history. All beta series reveal very high risk levels during 2008 and 2012/2013. Arguably, business risk in the maritime industry where highest during these times. Severely depressed freight rates in the spot and time-charter market, financial obligations resulting from newbuilding contracts entered during the shipping boom before 2007, an increasing vessel supply, new banking regulations tightening credit conditions, and an uncertain global economic situation have put enormous pressure on the shipping industry. This coincidence of high business risks at the industry level and the peak in estimated systematic risk levels support the hypothesis that time-varying market betas better describe the level of industry risks. Moreover, betas exhibit a cyclical rather than a merely volatile behavior for all segments of the industry, one that is clearly different from the S&P 500 and manufacturing firms benchmark. In fact, the average betas of the S&P 500 constituent firms are much smoother and less cyclical. The same applies to the behavior of systematic risk in the manufacturing industry.

A caveat is that our sample is unbalanced, with very few shipping companies listed in the early 1990s (or even before). Therefore, to take varying sample sizes into account, all figures, in addition to the beta estimates, also show the 90% confidence intervals. To control for potential listing effects in the evolution of the average beta estimate, we also analyze the systematic risk dynamics using a constant composition sample which only includes firms that span the entire sample period from 1990 through 2013. Panel B in Figure 2 reveals that the cyclical behavior is not attributable to a changing sample composition. The global cyclical pattern is similarly observable in the constant sample.

Figure 3 shows that the risk dynamics are homogeneous across shipping segment, but risk levels seem different. Moreover, the estimated betas in the different segments are very similar in low

[10] We exclude years prior to 1990 from this analysis to rely on a sufficient number of observations in a given year.

risk regimes, but the differences become more pronounced in high risk regimes. Besides these difference between shipping segments, we further observe that intra-segment heterogeneity slightly increases during crisis periods. Table 3 tabulates the average yearly beta estimates and the corresponding standard deviations for all shipping segments on a yearly basis. An interpretation is that increased industry risks affect the individual firms to a varying extent. We will discuss this issue further in the following section.

Overall, however, all segments of the shipping industry exhibit similar risk patterns. We attribute this finding to an industry cycle of risk rather than to a mere parallel shift in firm-level business risks. Accordingly, we interpret our results as showing evidence that the levels of systematic risk of firms from the shipping industry exhibit strong covariation. To the best of our knowledge, industry risk cycles based on individual firm's beta estimates have not been documented in the earlier literature.

5 Real determinants of systematic risk in the shipping industry

So far, our findings document considerable variation of systematic risk levels both over time and in the cross-section of shipping firms. Nevertheless, the relatively large standard deviations for betas in a given year (see Table 3) indicate that betas are not only dependent on time-related industry factors, but are also driven by additional factors that lead to different levels in systematic risk for firms in a given year. In this section, we thus analyze which factors account for the observed industry risk cycle, and which factors impact beta at the firm-level. We propose a testable model for systematic risk in shipping stocks based on the prior theoretical and empirical literature, and we evaluate the relative importance of potential beta determinants.

5.1 An empirical model of systematic risk

In the 1970s and the beginning of the 1980s, a strand of asset pricing literature turned to the analysis of the real determinants of systematic risk. Both firm-specific as well as macroeconomic variables were shown to explain variation in beta. Following Beaver et al. (1970), studies by Logue and Merville (1972), Breen and Lerner (1973), Rosenberg and McKibben (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 firm's systematic risk. In a nutshell, these studies provide empirical evidence that financial accounting variables are important for determining beta. More recent work decomposes beta into different components related to specific sources of risk.

For example, Campbell and Mei (1993) and Campbell and Vuolteenaho (2004) document that cash flow-related risks strongly affect firm's betas. Other studies focus on the impact of macroeconomic factors on systematic risk levels. Robichek and Cohn (1974) and Chen (1982) study the inflation rate and real income growth as potential determinants of beta, but do not find a robust relation in line with theoretical expectations. Fabozzi and Francis (1979) provide support for a general business cycle effect on systematic risk levels, but do not elaborate on the effective direction of macroeconomic influences. Using an extended version of the single-index market model that allows beta to change over different economic regimes by including a dummy variable, they document that systematic risk in single stocks experiences statistically significant shifts between expansion and recession periods. Using similar methodology, but allowing beta to interact with macroeconomic conditions, Abell and Krueger (1989) find that industries are affected by different macroeconomic factors. In another strand of literature, most related to our study, Andersen et al. (2005) model time-varying systematic risk in a state-space framework assuming that macroeconomic factors directly impact the stochastic process underlying beta. In line with theoretical predictions by Constantinides and Duffie (1996), they provide evidence for a counter-cyclical behavior of risk.

However, existing empirical evidence is mostly based on cross-sectional analyses, which do not explicitly account for the variation of beta over time. We build a panel model of systematic risk in the shipping industry, accounting for both cross-sectional and time series variation of betas. In particular, we model betas as a function of firm-specific and macroeconomic variables, which have been shown to influence beta in the cross-section. In addition, we incorporate an industry-specific time-varying factor that proxies for the shipping industry's business conditions. We also control for institutional differences by including variables that account for the influence of financial system characteristics in a firm's country of listing. Formally, the estimated beta is modeled as:

$$\hat{\beta}_{i,t} = X_{i,t}\gamma + F_t\delta + I_i\varphi + \varepsilon_{i,t} \tag{5}$$

where t describes the fiscal year-end month of firm i at year t, $\hat{\beta}_{i,t}$ is the conditional estimate of beta from the Kalman filter 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. The vectors γ, δ, and φ include regression coefficients for the respective factor portfolios, and $\varepsilon_{i,t}$ is the error term.

We use annual accounting data from Compustat Global to calculate firm-specific financial variables. Detailed construction principles are described in the following section. Conditional beta estimates are obtained via Kalman filtering (see Section 4). Annual accounting data and monthly betas are merged on a fiscal year-end basis. We eventually obtain a firm-year panel with betas and firm fundamentals at fiscal year-ends, which is further extended by macroeconomic and institutional variables. Data sources for macroeconomic and institutional factors are described below.

5.1.1 Firm-level factors

Previous empirical studies investigating the impact of firm characteristics on systematic risk examine different sets of financial variables. Beaver et al. (1970) chose seven financial variables. The study by Logue and Merville (1972) contains five financial variables, Breen and Lerner (1973) include seven firm-specific risk measures, and Melicher (1974) even examine a total of 26 accounting variables. Beaver et al. (1970) argue that accounting risk measures are expected to capture the uncertainty associated with corporate income streams. Given that the chosen financial factors are surrogates of the total variability of a firm's return on common equity, they should reflect both systematic and idiosyncratic components of risk and account at least for partial variation in systematic risk levels of corporations. We borrow from the existing literature and include the most commonly used firm-level variables into our panel regression model. Our list is not exhaustive, but we argue that it reflects a large proportion of the degree of uncertainty inherent in a firm's business model.

In particular, 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 firm. Research that explicitly focuses on these two components of risk include Hamada (1972), Lev (1974), Chance (1982), Hill and 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 the asset and capital structure on systematic risk. They highlight that both types of leverage magnify a firm's business risk. In line with prior evidence by Hamada (1972) and Lev (1974), Mandelker and Rhee's (1984) findings suggest that DOL and DFL explain a large proportion in the variation of beta. They document a positive impact on beta in both cases.

In measuring operating and financial leverage, we follow the approach suggested by O'Brien and Vanderheiden (1987), which has been frequently applied in the recent literature.[11] They suggest estimating DOL and DFL using a two-step time series regression setup that accounts for time trends in accounting data. The first step requires running the following three regressions:

$$ebit_t = ebit_0 + g_{ebit}\tau + \mu_{t,ebit} \tag{6}$$

$$sales_t = sales_0 + g_{sales}\tau + \mu_{t,sales} \tag{7}$$

$$eait_t = eait_0 + g_{eait}\tau + \mu_{t,eait} \tag{8}$$

where $ebit$ is the natural logarithm of earnings before interest and tax, $sales$ is the natural logarithm of sales, and $eait$ is the natural logarithm of earnings after interest and tax. Moreover, τ includes a time index and g is a regression coefficient capturing the estimated average annual growth rate of the respective factor. Equations (6), (7), and (8) can be easily estimated via OLS regressions of the respective log variables on a time trend.[12] Given the three residual series $\mu_{t,ebit}$, $\mu_{t,sales}$, and $\mu_{t,eait}$ from these regressions, in a subsequent step, DOL and DFL can estimated from the following two equations:

$$\mu_{t,ebit} = \gamma_{OL}\mu_{t,sales} + \varepsilon_t \tag{9}$$

$$\mu_{t,eait} = \gamma_{FL}\mu_{t,ebit} + \upsilon_t \tag{10}$$

where γ_{OL} and γ_{FL} are regression coefficients providing the estimates for DOL and DFL, respectively. ε_t and υ_t are Gaussian white noise. DOL measures the average sensitivity of the percentage deviation of earnings before interest and tax from its trend relative to the percentage deviation of sales from its trend, while DFL measures the average sensitivity of the percentage deviation of earnings after interest and tax from its trend relative to the percentage deviation of earnings before interest and tax from its trend. Using the appropriate data items from Compustat Global, we estimate

[11] For a recent application in the context of operating leverage, see Garcia-Feijoo and Jorgensen (2010).

[12] To compute logs of negative earnings, we follow Ljungqvist and Wilhelm (2005) and use a transformation common in accounting research: $ebit = ln(1+EBIT_t)$ if $EBIT \geqslant 0$ and $ebit = -ln(1-EBIT_t)$ if $EBIT < 0$. The same transformation is used for $EAIT$.

Equations (9) and (10) for five-year overlapping time intervals at the firm-level to derive parameter estimates for DOL and DFL at the end of each fiscal year (and for each firm).

Corporate liquidity. Corporate liquidity ratios may affect systematic risk levels through two channels. On the one hand, one could argue that current or liquid assets provide less volatile stock returns than non-current assets. Beaver et al. (1970) use the example of cash as the most liquid asset to highlight that current assets may have an expected return of zero with zero volatility (ignoring purchasing power parity). Therefore, one expects firms with larger proportions of current assets to have less volatile overall equity returns and arguably lower levels of systematic risk. On the other hand, firms with a higher liquidity ratio may be more flexible in crisis periods and less sensitive to fluctuations in the economy, also implying a lower beta. We test for the influence of liquidity on systematic risk by including a firm's current ratio into our model, defined as current assets divided by current liabilities.

Growth opportunities. Prior empirical studies (Beaver et al. (1970) among others) document a positive correlation between beta risk and growth in assets or growth in earnings. Growth can be interpreted as an investment in new projects with higher expected returns and also higher risks, which ultimately lead to a change in a firm's business risk. Moreover, growth firms may face higher levels of market competition than their mature counterparts, also implying higher levels of systematic risk in a firm's common stock. As standard in the literature, we model growth opportunities using the market-to-book ratio, arguing that growth firms are expected to have higher market-to-book ratios, on average. Specifically, we define a dummy variable to indicate high growth firms. A company is classified as a high growth firm if its market-to-book ratio is in the upper thirty percentile in a given year.

Payout. The payout ratio has been used in several earlier studies, most of which indicate a negative relation between dividend payment and the level of systematic risk. For example, Beaver et al. (1970) and Bowman (1979) argue that dividends may not directly affect beta, but convey information regarding future earnings to the market. The former study further suggests that, given firms pursue a policy of dividend stabilization, a high payout ratio today might be viewed as a signal for the managements perception regarding the uncertainty of future income streams. This argument is supported by the empirical evidence showing that dividend payout adjusted for comovement with earnings does not have any impact on systematic risk. Accordingly, one expects that the dividend payout is negatively correlated with beta. We measure 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 explain the size and book-to-market effects (Dichev (1998), Vassalou and Xing (2004), among others). However, the empirical evidence is ambiguous. While Dichev (1998) does not find any significant relationship between the probability of default and the cross-section of stock returns, results in Vassalou and Xing (2004) indicate that the size and book-to-market factors in the Fama and French (1993) model reflect large proportions of default risk. This latter finding supports evidence in Lang and Stulz (1992) and Denis and Denis (1995), showing that the probability of default is related to aggregate macroeconomic factors and thus may be systematic. Most recently, Benmelech and Bergman (2011) describe an intra-industry collateral channel through which a bankrupt firm imposes negative externalities on its 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. Arguably, this collateral channel is particularly severe in asset intensive industries (Pulvino (1998)), such as the shipping industry. Therefore, we hypothesize that the probability of a corporate default is an underlying firm-specific, but ultimately also industry-related driver of beta. To control for the probability of bankruptcy, we use Altman's (1968) Z-score and separate firms into groups with high (low) bankruptcy probability scores. 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.

5.1.2 Macroeconomic factors

In addition to firm-level factors, our model also contains macroeconomic variables, which account for the level of uncertainty induced by the overall economy. Prior literature that has examined the effect of economic conditions on the variation in beta coefficients is limited, and the empirical evidence is not conclusive. Existing studies use different factor sets as proxies for the state of the economy, but most agree on industrial production and inflation as relevant variables. In our study, we use five macroeconomic factors to control for broader economy-related effects in beta risk: (1) freight rate volatility, (2) credit spread, (3) industrial production growth, (4) inflation rate, and (5) exchange rate volatility. Arguably, these variables reflect industry-specific and global macroeconomic risk factors.

Given the documented cyclical behavior of systematic risk in shipping, we argue that industry-specific factors are expected to be important drivers of shipping firms' betas. Freight rates are the result of the supply and demand balance on global freight markets, and the state of the freight markets can be viewed as a major determinant of business conditions in the shipping industry. Freight rate volatility can serve as a proxy for the industry's core business risk. Freight rates exhibit volatility clustering, i.e. there are periods of high and low freight rate volatility (Alizadeh and Nomikos (2012), Drobetz et al. (2012), among others). As times of high (low) freight rate volatility should be characterized by high (low) levels of investor uncertainty about future earnings of shipping companies, we expect beta to be higher (lower) during such periods. Put differently, freight rate volatility might reflect cycles of industry business risk, which have a direct impact on firms' betas. Accordingly, we rely on freight rate volatility to proxy for industry-related risks. Using the Clarksea index (CSI) as the proxy for the average charter rate over all industry 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 CSI is obtained from Clarkon's Shipping Intelligence Network.

We further include the credit spread as a proxy for potential global financing risks. Shipping is an asset intensive business, involving large investments in modern fleets and efficient technology to ensure competitiveness in the international freight market. Both a lack of available financing and extremely high financing costs may result in the postponement of essential investment projects, which leads to an increasing uncertainty about future income streams. Similarly, the high levels of industry financial leverage and the long horizons for vessel investments make the availability of refinancing at favorable conditions essential for the industry. Higher refinancing costs or unavailablethe lack of refinancing may ultimately result in sales of important assets at fire-sale prices (Brunnermeier and Yogo (2009) and Choi et al. (2014)) or even in financial distress and inefficient liquidation of firms (Diamond (1991, 1993)), eventually increasing the ex-ante uncertainty about the continuation value of the firm. Therefore, financing risk should be an important industry-specific risk factor in the shipping industry that may drive the observed cyclicality in systematic risk levels. Following the empirical literature, we measure the credit spread as the return differential between long-term BAA-rated and long-term AAA-rated corporate bonds. The data on bond returns is from the Federal Reserve's Board of Governors database.

To isolate a potential industry cycle effect in beta risk from overall economy effects, the remaining factors control for global macroeconomic sources of risk that affect investor uncertainty about future corporate income streams. To avoid multicollinearity problems, the set of global macroeconomic factors is limited to three variables. 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, and the volatility of the exchange rate of the US$ to major currencies (reflecting uncertainty about the value of earned income streams in local currency) as explanatory variables in our model. Data on industrial production and inflation is obtained from the OECD database, while the exchange rate of the US$ against major currencies is from Thomson Financial Datastream.

5.1.3 Institutional factors

Prior empirical studies focus on firm-specific and in parts on macroeconomic determinants of systematic risk. However, betas may also vary across different institutional environments. The literature on the relation between law and finance, starting with La Porta et al. (1998), provides evidence for different quality standards of legal systems around the world. For example, the legal protection guaranteed to investors is different across legal systems, with common law countries providing higher investor protection than civil law countries. When the rights of outside investors are better protected by the law, they are willing to pay more for financial assets. Investors pay more because they recognize that, with better legal protection, more of the firm's profits would come back to them as interest or dividends as opposed to being expropriated by the entrepreneur or the managers who control the firm. By limiting expropriation, the law raises the price that securities fetch in the marketplace. From an investor perspective, weak legal protection of financial claims against third parties is investment risk, which investors cannot fully hedge, thus legal risk is (at least partly) systematic and increases beta risk. Consistent with this view, La Porta et al. (2002) find evidence for a higher valuation of firms in countries with better protection of minority shareholders (i.e., in common law countries compared to civil law countries). Directly estimating firm's cost of capital (rather than valuation levels), Hail and Leuz (2006) show that firms from countries with more extensive disclosure requirements, stronger securities regulation, and stricter enforcement mechanisms have a significantly lower cost of capital. Lambert et al. (2007) examine whether and how different quality of accounting information about a firm in different legal environments manifests in its cost of capital. They demonstrate that a direct effect occurs because higher quality disclosures reduce a firm's covariances with other firms' cash flows, which is non-diversifiable and thus systematic. An indirect effect occurs because higher quality disclosures affect a firm's real decisions, which likely changes the firm's ratio of the expected future cash flows to the covariance of these cash flows with the sum of all the cash flows in the market. Lambert et al. (2007) derive conditions under which an increase in information quality, which arguably depends on the institutional environment, leads to an unambiguous decline in the cost of capital.

The literature provides different measures for the quality of the legal system, legal enforcement standards, and reporting standards. In our analysis, we control for creditor and shareholder rights in a firm's country of listing, since these two factors presumably are the most important to corporate shareholders. Based on the empirical findings in the literature, we expect that firms listed in countries with weak shareholder rights and/or strong creditor rights exhibit higher levels of systematic risk. We further add a control variable for the financial system in place, attempting to cover potentially omitted variables. The variable is binary and takes a value equal to one for market-based financial systems, and zero otherwise. To proxy for creditor and shareholder rights, we use 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 again use dummy variables to indicate countries with high legal standards. Countries with creditor rights index values of 3 and 4 are defined as countries with strong creditor rights. Similarly, countries with shareholder index values of 4 and 5 are classified as having strong shareholder rights.

5.2 Empirical results

The following two sections discuss the empirical results for our panel regression model. First, we provide regression results for the different factor sets as well as the full model and analyze the impact of each individual factor. For comparison reasons, we further estimate the model for the benchmark sector of manufacturing firms in order to demonstrate that risk driver in shipping are substantially different from other industries. In a second step, we analyze the explanatory power of the model and the relevance of the different factor sets in predicting beta variation. Both steps allow us to identify the most relevant factors in explaining the behavior of systematic risk levels, in the cross-section of firms and over time.

5.2.1 Systematic risk model estimates

We use the model in equation (5) together with the variables defined above to estimate the real determinants of beta. To control for unobserved heterogeneity across operating segments (i.e., bulk, container, tanker, and diversified), we include segment-fixed effects by demeaning both the dependent variable and the explanatory variables with respect to the respective group mean. We note that the estimated betas involve measurement errors by nature. Specifically, risk estimates exhibit varying degrees of precision across observations. To account for the introduced heteroskedasticity and the resulting inefficiency of standard OLS, we follow Dahlquist et al. (2000) and use a weighted least squares (WLS) approach to obtain coefficients estimates for our systematic risk model. The weighting of each observation is set to the inverse of the standard error of the Kalman-filtered beta estimated in Section 4.

Table 4 reports the model estimates for our set of shipping companies and the benchmark sector. To ease interpretation and comparison of the estimated regression coefficients, we provide standardized regressions coefficients (except for the binary factors).[13] Firms must have non-missing data on all firm-specific variables to be included in the initial regression sample. The sample period is restricted to the years 1990 through 2013 due to limited data availability in the years prior to 1990.

[Insert Table 4 here]

Column (2) shows that there is a statistically significant impact of all firm-level factors on beta except for liquidity. In line with theoretical expectations, operating and financial leverage constitute sources of corporate systematic risk; the relation is positive in both cases and highly statistically significant at the 1% level. In addition, firms having high payout ratios and high corporate liquidity exhibit lower beta risk, while firms with high growth opportunities and a high default risk are exposed to higher levels of systematic risk.

Column (3) reports the coefficient estimates for the set of macroeconomic factors. Both industry-specific risk characteristics (freight rate volatility and credit spread) and the business cycle (industrial production growth) reveal to have an impact on beta. We observe higher levels of beta during years of high freight rate volatility and through economic downturns. Both coefficients are positive and highly statistically significant. These findings are in line with our observation in Section 4, where we note that levels of systematic risk were highest during the recent shipping crisis. Further, they confirm prior empirical evidence by Lettau and Ludvigson (2001a) as well as by Andersen et al. (2005) and Constantinides and Duffie (1996), who document a counter-cyclical behavior of stock returns and market risk, respectively. Furthermore, refinancing risks, as measured by the credit spread, influence beta. The estimated coefficient indicates higher betas during times of higher credit spreads. In contrast, inflation rates and the US$ exchange rate are of minor importance. Overall, two out of three macroeconomic variables that reveal to have a statistically significant influence on systematic risk levels in the shipping industry describe industry-specific risk factors.

[13]Standardizing coefficient involves normalizing the variance of all variables to unity. Standardized coefficients describe the effect of a one standard deviation change in the explanatory variable on the dependent variables (expressed in terms of standard deviations).

Finally, regressing estimated risk levels on the complete factor set, the results remain qualitatively unchanged. However, some of the factors exhibit a decrease in statistical significance. Most important, the coefficient on payout drops substantially and becomes insignificant. Furthermore, the coefficient on default risk exhibits a decrease in magnitude when we control for economy- and industry-related factors. Overall, the full model results reveal that eight factors are of major importance in determining beta, all being highly statistically significant. Operating leverage, financial leverage, corporate growth opportunities, and default risk influence systematic risk on the firm-level. In addition, industry conditions (freight rate volatility and credit spread) and the business cycle (industrial production growth) seem to be aggregate drivers of beta over time.

Regarding the set of institutional factors, Column (4) suggests that creditor rights affect systematic risk. We find a significantly positive relation between creditor rights and beta, supporting our conjecture that strong creditor rights increase the investment risk of equity investors. On average, the difference in estimated betas between countries with weak and those with strong creditor rights is 0.246. To the best of our knowledge, a similar effect has not been documented in the literature so far. In contrast, shareholder rights seem to play a minor role. Finally, the financial system control variable loads positively. Given its multidimensional nature as a control for different dimensions of the financial system in place, however, an unambiguous economic interpretation is difficult.

Finally, comparing our results for shipping companies with the benchmark sector in Column (1) indicates that systematic risk levels in shipping seem to have specific determinants. Coefficients between Column (1) and (4) differ substantially. This holds in particular for the shipping-specific variables, i.e., operating and financial leverage as well as industry and macroeconomic factors.

5.2.2 In-sample predictions of systematic risk behavior

To develop a more detailed understanding of the model's explanatory power, we next analyze in-sample predictions of systematic risk levels. We use the full model specification (see Column (4) in Table 4) to obtain linear predictions of beta values in a given firm-year. Figure 4 presents average estimated and predicted beta series over the sample period from 1990 through 2013 for the full sample of shipping companies. Looking at estimated and predicted betas (Panel A), the plot reveals that the model performs quite well in predicting the cyclical behavior of estimated betas.[14]

In a second step, we split beta predictions into a firm-specific, an industry-related, and a macroeconomic component and compute the predicted time-series for each set of factors based on the full model coefficient estimates. To investigate the individual series' contributions to the overall variation in predicted beta, Panels (B) to (D) plots these conditional beta series together with the full model predictions in terms of deviations from individual series' means for the full model as well as for the three subsets of explanatory variables. The results show that the beta evolution from 1990 through 1995, but especially the downturn in predicted beta during the 1996-2002 period and the following moderate beta regime from 2003 to 2006 may be attributed to firm-specific, macroeconomic, and industry-related effects altogether. Similar patterns are observable for the final two sample years. In contrast, the sharp increase in the levels of systematic risk from the beginning of

[14]Untabulated results show that the beta predictions generated through the systematic risk model a significantly superior to those obtained from a no-change model.

the crisis in 2007 onward is solely driven by industry conditions (freight rate volatility and financing risk). Surprisingly, firm-specifics and other macroeconomic factors do not account for the increase in beta during these times.

Overall, our results provide evidence for a significant impact of industry-specific conditions on the betas of shipping companies. In particular, the empirical findings suggest that industry conditions are primarily important factors in explaining high risk regimes in the shipping industry. Accounting for both cross-sectional and time-series variation in estimated betas and controlling for global macroeconomic effects as well as the institutional environment a company operates in, we further confirm that firm-specific real determinants 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.

6 Conclusions

This paper analyzes stock market betas in the shipping industry. Using a sample of 150 globally-listed shipping companies, we examine the variability of beta over time. Using Kalman filtering, we obtain monthly conditional beta estimates. Although we find strong intra-industry heterogeneity of beta risk across the individual firms, our time-series analysis reveals a considerable industry cycle of beta risk, which is similar over the different industry segments (bulk, container, and tanker shipping), but different from the time development of beta of the average industrial company (approximated by the average S&P 500 firm).

Finally, we analyze the real determinants of beta. Our results show that firm-specific, industry-related as well as macroeconomic and institutional variables play an important role in determining beta. Our empirical model well explains the observed cyclicality in betas. We provide empirical evidence beyond the existing literature and show that industry factors play a major role in explaining high risk regimes.

Our results support the view that market betas reflect the underlying business risk of a firm. Panel regression results show that the drivers of systematic risk are different in nature, origin, and strenght, with macroeconomic and industry-level effects playing a major role.

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Tables

Table 1
Sample overview

The table shows the distribution of firms and firm-year observations in our sample with respect to the firms' ISIN-issuing country. The sample consists of 150 listed shipping companies from 35 countries. Monthly firm data are obtained from Thomson Financial Datastream. The sample period is from January 1973 through August 2014. ISIN-based country classifications may be different from the companies' countries of incorporation.

Country (ISIN)	Companies	Calendar year	Firm-years
Asia	50	1973	8
BGD	1	1974	8
CHN	8	1975	8
HKG	1	1976	9
IDN	1	1977	9
IND	5	1978	9
JPN	8	1979	10
KOR	5	1980	11
MYS	5	1981	12
PAK	1	1982	12
PHL	1	1983	14
SGP	2	1984	18
THA	3	1985	18
TWN	9	1986	19
		1987	20
Europe	34	1988	22
BEL	2	1989	33
DEU	3	1990	40
DNK	5	1991	44
IRL	1	1992	50
ITA	1	1993	54
LUX	1	1994	60
LVA	1	1995	66
NOR	13	1996	73
SWE	7	1997	80
		1998	82
North America	14	1999	82
CAN	1	2000	80
USA	13	2001	83
		2002	82
Other Countries	52	2003	83
ARE	1	2004	92
BHS	1	2005	111
BMU	14	2006	116
CHL	1	2007	128
CYM	2	2008	133
JEY	1	2009	133
JOR	1	2010	131
LBR	4	2011	129
MHL	25	2012	126
QAT	1	2013	123
SAU	1	2014	118
Total	**150**	**Total**	**2539**

Table 2
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, and the risk-free asset over the sample period.

					Percentiles			
	N	Mean	SD	Median	25th	75th	Min	Max
Segment								
Bulk	5,315	-0.005	0.175	0.000	-0.081	0.072	-0.653	0.575
Container	3,442	-0.002	0.149	0.000	-0.071	0.070	-0.511	0.472
Tanker	5,726	-0.007	0.146	0.000	-0.070	0.066	-0.548	0.424
Diversified	14,531	0.001	0.137	0.000	-0.067	0.069	-0.440	0.442
Total	29,014	-0.002	0.148	0.000	-0.070	0.069	-0.653	0.575
Benchmarks								
MSCI World	500	0.008	0.044	0.012	-0.016	0.034	-0.210	0.137
Risk-free rate	500	0.004	0.003	0.004	0.002	0.006	0.000	0.014

Table 3
Dynamic beta estimates over the sample period

The table reports average annual market betas for each sample year as well as the respective standard deviations. Annual betas are calculated as the mean value of monthly Kalman filter estimates from the respective year. We provide statistics 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.

	Bulker		Container		Tanker		Diversified		Total	
	$\bar{\beta}$	SD	$\bar{\beta}$	SD	$\bar{\beta}$	SD	$\bar{\beta}$	SD	$\bar{\beta}$	SD
1990	0.818	0.788	1.204	0.279	0.927	0.307	1.032	0.893	1.000	0.734
1991	0.708	0.896	1.135	0.209	0.802	0.404	0.985	0.935	0.925	0.803
1992	0.753	0.733	1.038	0.210	0.807	0.368	0.924	0.935	0.883	0.783
1993	0.721	0.635	1.161	0.436	0.792	0.317	0.778	0.889	0.802	0.741
1994	0.751	0.520	1.091	0.441	0.818	0.296	0.700	0.751	0.759	0.630
1995	0.651	0.486	0.869	0.407	0.729	0.352	0.671	0.643	0.695	0.544
1996	0.580	0.484	0.646	0.501	0.738	0.367	0.630	0.570	0.644	0.508
1997	0.527	0.453	0.507	0.414	0.704	0.410	0.576	0.520	0.583	0.473
1998	0.546	0.418	0.534	0.446	0.597	0.382	0.602	0.564	0.583	0.489
1999	0.524	0.459	0.524	0.480	0.618	0.373	0.615	0.578	0.589	0.506
2000	0.514	0.553	0.546	0.513	0.661	0.354	0.647	0.536	0.613	0.503
2001	0.697	0.558	0.571	0.437	0.664	0.327	0.707	0.529	0.680	0.487
2002	0.920	0.603	0.642	0.416	0.748	0.366	0.767	0.561	0.772	0.519
2003	1.063	0.705	0.735	0.444	0.810	0.352	0.939	0.574	0.907	0.547
2004	1.218	0.893	0.792	0.475	0.903	0.418	1.041	0.595	1.011	0.616
2005	1.110	0.549	0.854	0.503	1.011	0.479	1.086	0.533	1.043	0.519
2006	1.421	0.616	1.130	0.382	1.025	0.448	1.211	0.588	1.206	0.555
2007	1.623	0.708	1.310	0.644	1.018	0.459	1.252	0.598	1.284	0.625
2008	1.632	0.876	1.276	0.595	1.039	0.448	1.265	0.570	1.292	0.648
2009	1.432	0.898	1.159	0.410	0.968	0.427	1.120	0.511	1.163	0.610
2010	1.252	0.773	1.085	0.377	1.085	0.487	1.053	0.488	1.109	0.554
2011	1.288	0.719	1.180	0.475	1.252	0.715	1.088	0.488	1.179	0.596
2012	1.428	0.854	1.127	0.449	1.319	0.794	1.130	0.524	1.234	0.665
2013	1.486	0.941	1.028	0.498	1.226	0.815	1.144	0.541	1.221	0.708
2014	1.472	0.967	0.990	0.508	1.058	0.410	1.128	0.554	1.178	0.666

Table 4
Determinants of beta

The table reports regression results for market beta determinants. Monthly Kalman filter-estimated betas 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 5.1). We report standardized regression coefficients for all non-binary variables. All regression specifications include segment-fixed effects. Standard errors controlling for clustering at the firm level are reported in parentheses. ***, ** and * denote statistical significance at the 1%, the 5% and the 10% level, respectively.

	Manuf.	Shipping companies		
	(1)	(2)	(3)	(4)
(A) Firm-specific variables:				
Degree of operating leverage	0.018***	0.146***	0.099***	0.169***
	(0.001)	(0.002)	(0.002)	(0.003)
Degree of financial leverage	0.041***	0.105***	0.104***	0.138***
	(0.003)	(0.008)	(0.008)	(0.009)
Corporate liquidity	0.001	−0.039**	−0.035**	−0.040*
	(0.003)	(0.002)	(0.002)	(0.002)
Growth opportunities	0.028***	0.038*	0.101***	0.281***
	(0.009)	(0.022)	(0.022)	(0.031)
Payout	−0.126***	−0.113***	−0.146***	−0.036
	(0.009)	(0.020)	(0.020)	(0.030)
Default risk	0.116***	0.130***	0.067***	0.094***
	(0.034)	(0.021)	(0.021)	(0.032)
(B) Macroeconomic variables:				
Freight rate volatility	0.028***		0.135***	0.084**
	(0.004)		(0.011)	(0.014)
Credit spread	0.064***		0.142***	0.107***
	(0.011)		(0.023)	(0.031)
Industrial production growth	−0.005***		−0.134***	−0.145***
	(0.001)		(0.002)	(0.003)
Inflation	−0.055***		0.022	−0.030
	(0.005)		(0.012)	(0.014)
US Dollar exchange rate volatility	−0.029**		−0.011	0.014
	(0.012)		(0.027)	(0.037)
(C) Institutional variables:				
Shareholder rights				0.040
				(0.060)
Creditor rights				0.246***
				(0.034)
Financial system				0.170***
				(0.030)
Industry/Segment-fixed effects	Yes	Yes	Yes	Yes
Adj. R-squared	0.062	0.052	0.106	0.167
Observations	4,773	1,363	1,363	945

Figures

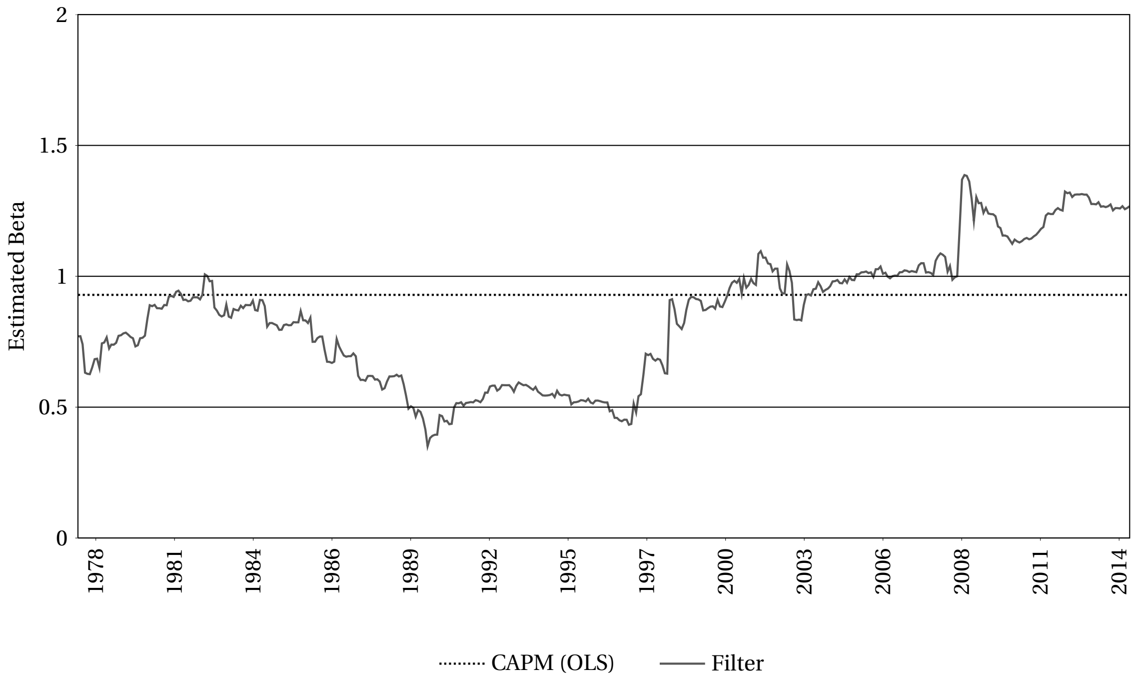

Figure 1. Overview of beta estimates for A.P. Møller-Mærsk A/S. The figure presents the time-series estimates for A.P. Møller - Mærsk A/S over the full sample period from January 1973 through August 2014. We dropped the first 12 observations of the Kalman filter estimates to account for initialization of the filter algorithm.

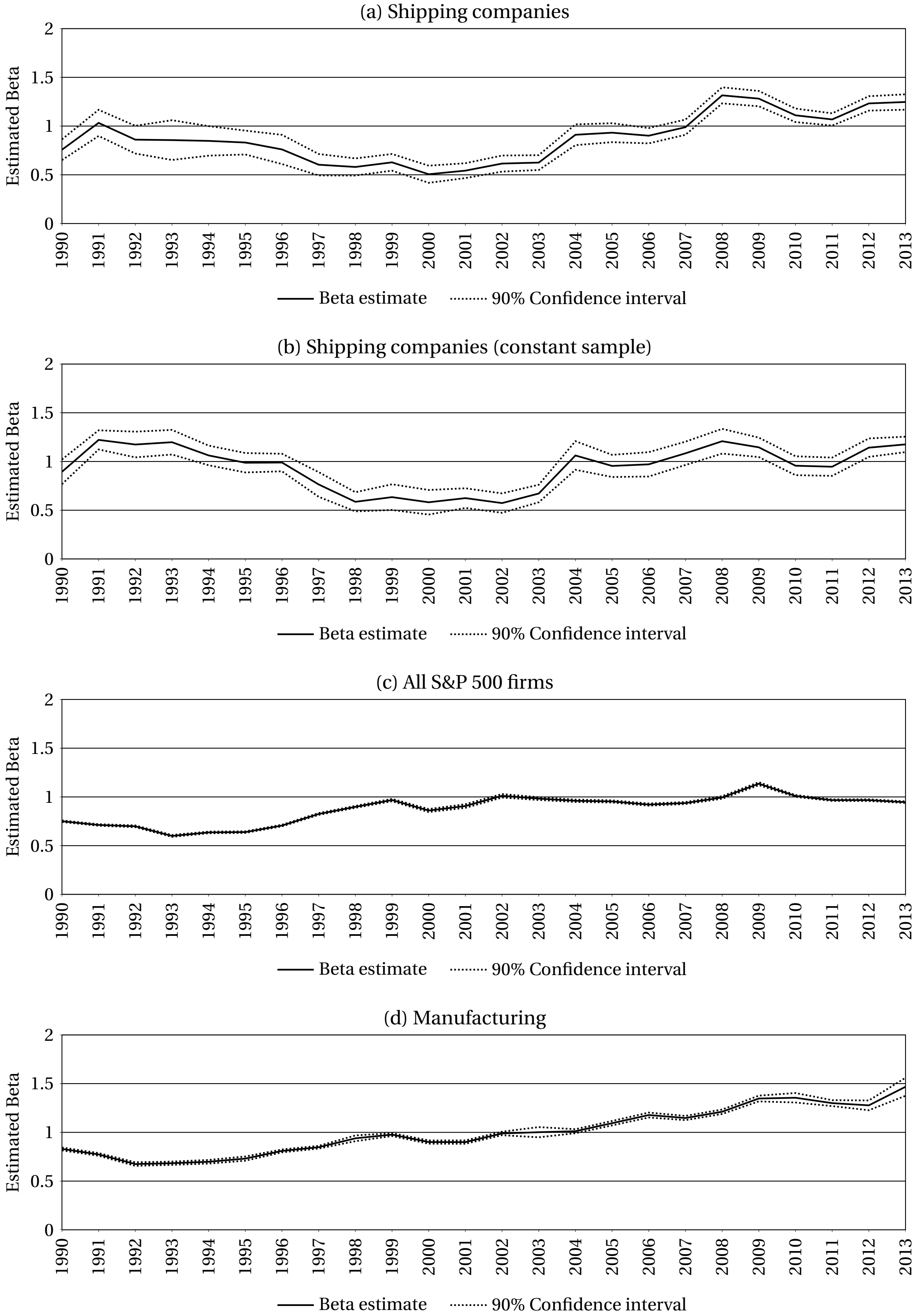

Figure 2. Beta estimates of shipping companies and benchmark industries over time. The figure shows average annual market beta estimates over time for the sample of shipping companies, the average S&P 500 company, and all manufacturing firms contained in the S&P 500. Industry classification follows the definition of Fama and French (1997). Benchmark betas are estimated based on monthly historical data of all S&P 500 companies which are or have been active in the index or benchmark industry, respectively. The sample period is limited to the years 1990 through 2013 due to limited observations for our shipping sample prior to 1990. Panel B shows the beta dynamics of all shipping firms which have constantly been in the sample from 1990 until 2013.

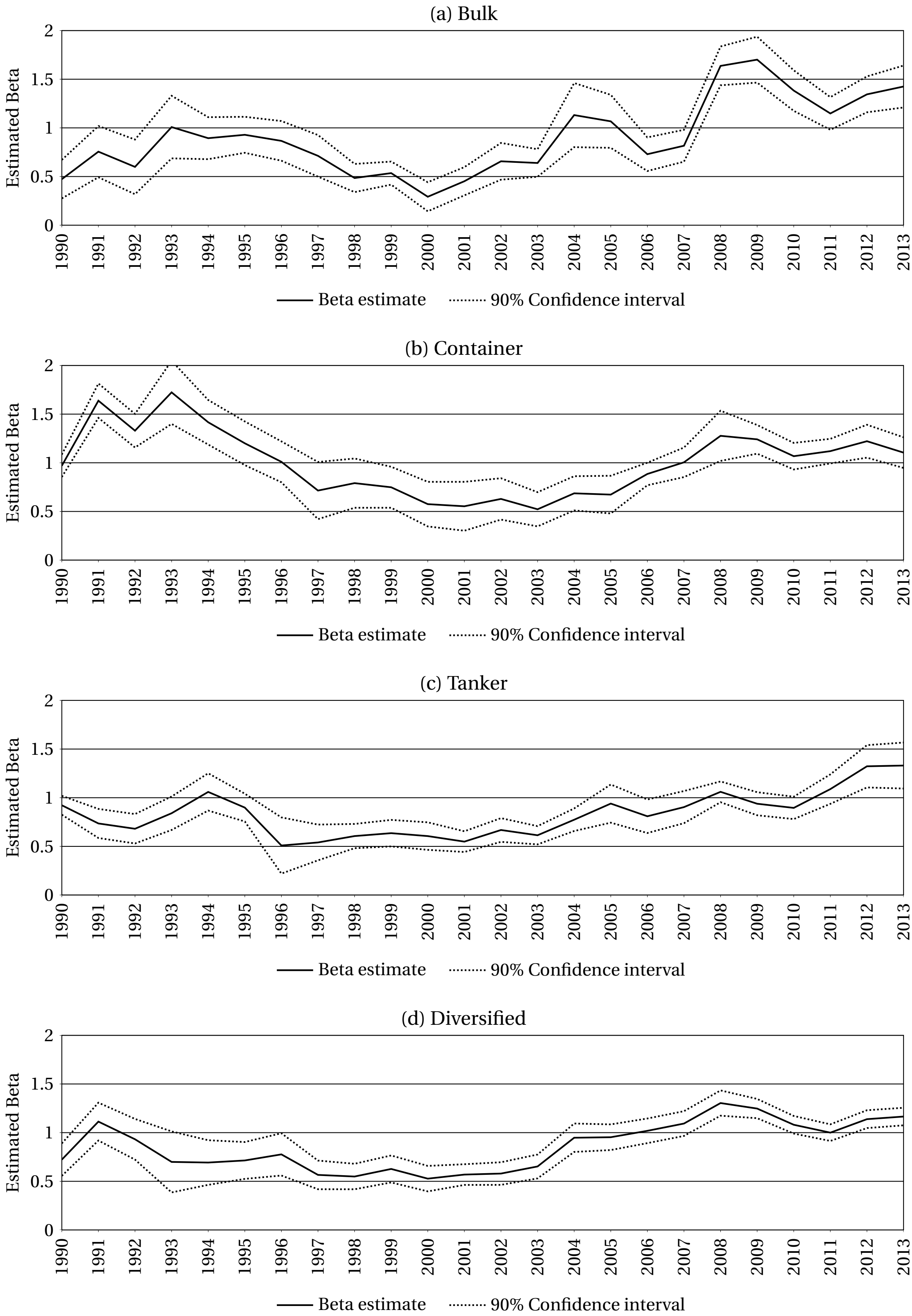

Figure 3. Beta estimates by segment over time. The figure shows average annual market beta estimates over time separately for the four shipping segments. The sample period is limited to the years 1990 through 2013 due to limited observations prior to 1990.

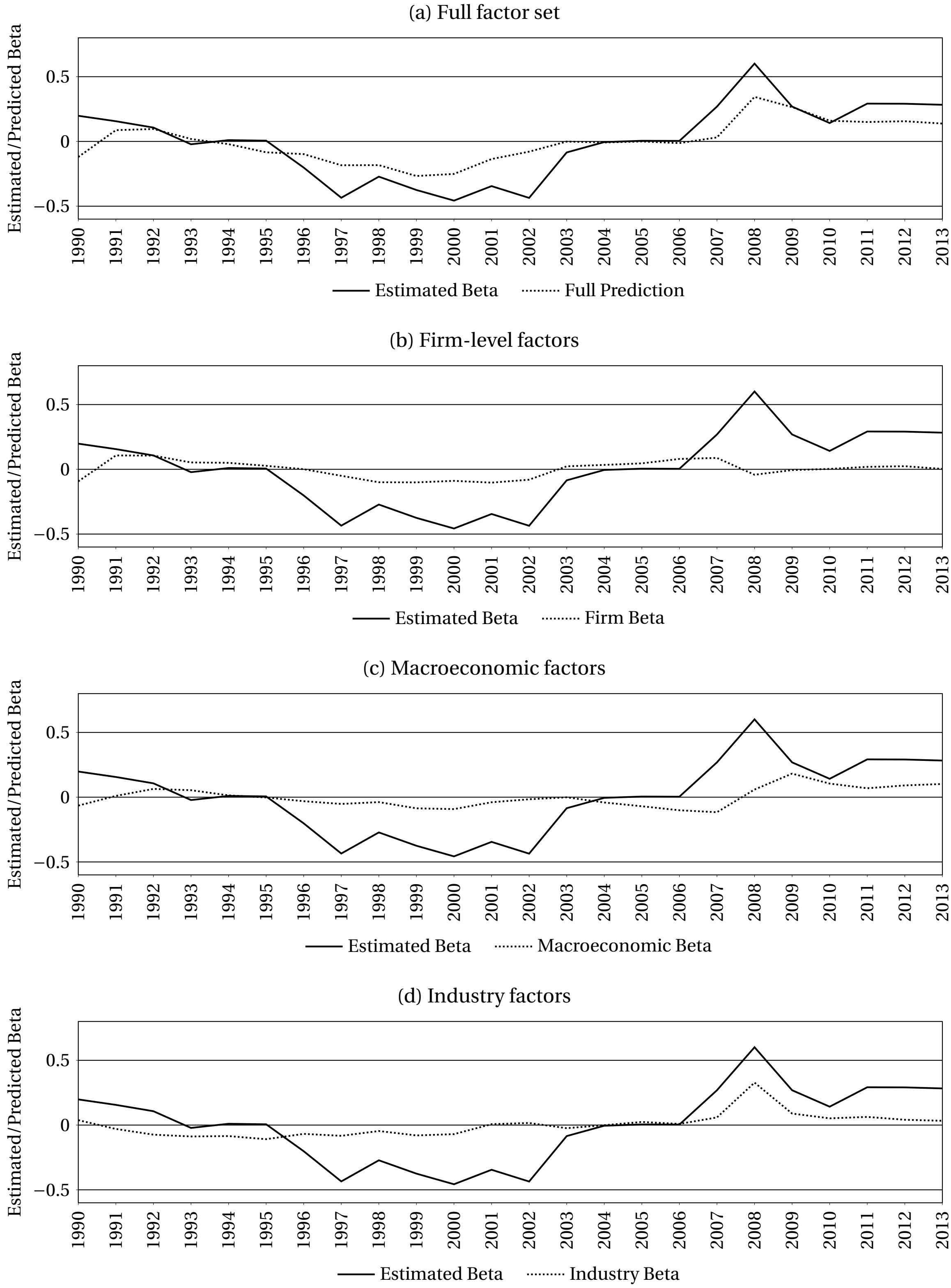

Figure 4. In-sample predictions of systematic risk behavior. The figure shows the estimated and predicted behavior of systematic risk. Estimated betas are those obtained via Kalman filtering. Linear predictions for beta are drawn from the full specification of the panel regression model in Table 4. Panels (a)-(d) describe beta variation in terms of deviations from individual series' means. The factor set-based series include beta predictions based on the estimated coefficients from the full model specification, but only using the different bundles of explanatory variables one at a time. The sample period is 1990 through 2013.