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Dynamic volatility spillovers across shipping freight markets

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ABSTRACT

This paper examines the existence of dynamic volatility spillovers within and between the dry-bulk and tanker freight markets by employing the multivariate DCC-GARCH model and the volatility spillover index developed by Diebold and Yilmaz (2012, 2009). This methodology is invariant to ordering the variables when estimating a VAR model and allows for the disaggregation of volatility spillovers in total, directional, net and net pairwise. Results reveal the existence of large time-varying volatility spillovers across shipping freight markets, which are more intense during and after the global financial crisis.

1. Introduction

Transportation by sea is the leading mode of transportation worldwide carrying over 90% of the global trade in volume terms (World Trade Organization, 2014). A distinct feature of the shipping industry, which facilitates sea transportation, is its pronounced segmentation as the demand for the transportation service fluctuates per type and volume of cargo transported. This segmentation effect stems from the fact that the decision to hire a certain type of vessel for ocean transportation of a certain commodity depends on at least four main factors: (i) the type of the commodity transported, (ii) the commodity parcel size (iii) the route and (iv) the loading/unloading port facilities (Alizadeh and Nomikos, 2009). Thus, the shipping sector is divided into different segments and sub-segments according to the transported cargo and size[1] of vessels, respectively. These segments and sub-segments typically follow quite distinct business cycles primarily driven by the demand for different commodities transported (Kavussanos and Visvikis, 2006). As a result, shipping freight rates, being the equilibrium prices of the transportation service also exhibit pronounced segmentation effects among different vessel types and sizes (Kavussanos, 2003, 1996).

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[1] Vessels employed in the liner sector are classified into Feeder (100–500 twenty-foot equivalent units or TEU), Feedermax (500–1000 TEU), Handysize (1000–2000 TEU), Sub-Panamax (2000–3000 TEU), Panamax (3000–4000 TEU) and Post-Panamax (more than 4000 TEU). The dry-bulk sector differentiates into five categories per cargo-carrying capacity: Handysize (20,000–35,000 dwt), Handymax (35,000–45,000 dwt), Supramax (45,000–55,000 dwt), Panamax (60,000–75,000 dwt) and Capesize (more than 80,000 dwt). The tanker sector is also classified in five sub-sectors: Handysize (20,000–45,000 dwt), Panamax (50,000–80,000 dwt), Aframax (80,000–120,000 dwt), Suezmax (130,000–160,000 dwt) and Very Large Crude Carriers (VLCC) (more than 160,000 dwt, typically around 250,000–300,000 dwt).

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However, despite the pronounced market segmentation observed in shipping freight markets, shipping segments and sub-segments are not completely isolated from each other (Stopford, 2009). This is due to the fact that different types of vessels can transport the same cargo and in this way create competition among different shipping sectors. In addition, investors have the option to reposition their investment from one shipping sector to another. In fact, several shipping companies are active in all shipping sectors and investors from one sector will enter another if they see an opportunity. In this way, supply and demand imbalances in one segment of the market soon ripple across to other segments. However, the extant literature remains silent regarding the dynamic evolution of shipping freight market segmentation over time. This paper aims to provide novel evidence of the segmentation effect in shipping freight markets by investigating the existence, the severity and the direction of dynamic volatility spillovers within the dry-bulk freight segment and between the dry-bulk segment and tanker sub-segments.

The investigation of volatility spillovers has a number of important implications for several participants in shipping and financial markets, such as shipowners, charterers, ship-lending financial institutions, investors and regulators alike. First, volatility serves as a measure of risk and for this reason potential volatility changes and spillovers across markets can have a major negative impact on risk-averse investors (Drobetz et al., 2010). Thus, the identification of volatility spillovers dynamics has important implications regarding portfolio diversification, hedging strategies and forecasting shipping freight rates. Further, as volatility is a crucial factor for pricing derivatives contracts, investigating volatility spillovers contributes to greater efficiency in the pricing of shipping freight derivatives (Kavussanos and Nomikos, 1999). Second, volatility spillovers indicate market co-movements which are particularly evident during crises events as the volatility increases sharply and spills over to other markets (Reinhart and Rogoff, 2008). For this reason, investigating and measuring volatility spillovers over time can lead to early signs of crises in the shipping freight rate markets and the eager adoption of hedging strategies by market participants and regulatory authorities. Third, shipping freight rates directly affect the cash flow generating ability of a shipping company,[2] forming a major concern of institutional and individual investors investing on shipping projects. This stems from the fact that shipping freight rates exhibit excess volatility along with a number of other unique characteristics.[3] For the reasons above, the investigation of volatility spillovers across shipping freight markets is extremely important for the participants in the shipping industry,[4] the global transportation network and the capital markets.

A number of studies have focused on modeling the volatility of shipping freight rates and identifying potential volatility spillovers across different shipping freight rates segments and sub-segments (Kavussanos, 1996, 1997, 2003; Alizadeh, 2001; Chen et al., 2010; Drobetz et al., 2012). However, previous studies on the issue do not estimate a generalized autoregressive conditional heteroskedasticity (GARCH) model that captures the effect of dynamic conditional correlations on the covariance matrix over time. In order to overcome this limitation and model the volatility of shipping freight rates effectively, this paper adopts the dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model as introduced by Engle (2002). In this way, asymmetries are incorporated in a broader fashion than in other types of multivariate GARCH models, i.e. the DCC-MGARCH model does not assume constant correlation coefficients over the sample period. Specifically, it allows for series-specific news shocks and smoothing parameters; takes into account conditional asymmetries in correlation dynamics and corrects for heteroskedasticity directly by using standardized residuals in the estimation of correlation coefficients.

Existing studies on the issue rely on vector autoregressive (VAR) and vector error correction models (VECM) to investigate volatility spillovers within shipping freight markets (Alizadeh, 2001; Chen et al., 2010). However, the results obtained when estimating the variance decompositions in a VAR model depend on ordering the variables (see, for instance, Diebold and Yilmaz, 2009). This is a crucial restriction of the Cholesky-factor identification of VAR models. In order to overcome this limitation, this paper adopts the Diebold Yilmaz (DY) volatility spillover index methodology, as developed originally in Diebold and Yilmaz (2009) and extended in Diebold and Yilmaz (2012) to be invariant to ordering the variables. Moreover, previous studies on the issue estimate static volatility spillovers through the estimation of GARCH-VAR models over the whole sample period (Kavussanos, 1996, 1997, 2003; Alizadeh, 2001; Chen et al., 2010). However, estimating static volatility spillovers exhibits limitations as it misses potential dynamics (Diebold and Yilmaz, 2012, 2009). Specifically, the possibility that shocks in one market could be attributed to time-varying volatility spillovers within and between different shipping freight markets segments and sub-segments. Furthermore, computing the average spillover effect (static) over a long and turbulent period might mask potential cyclical movements in spillover effects. Finally, previous studies on the issue are not able to quantify spillovers in sufficient detail, as estimates of VAR models and impulse responses do not provide a clear interpretation regarding the directional spillovers "from and to" each market over time. Again, the DY spillover index approach accommodates these limitations by allowing for the estimation of dynamic and directional volatility spillover effects over time and within and between different segments and sub-segments of the shipping industry, revealing spillover trends, cycles and bursts. In

[2] For an overview of ways to raise capital in the shipping industry see (Albertijn et al., 2011). Typically, access to finance can take different forms for a shipping firm, such as through initial public offerings (Kavussanos and Marcoulis, 2000), shipping bonds (Kavussanos and Tsouknidis, 2014) or shipping bank loans (Kavussanos and Tsouknidis, 2016).

[3] The excess volatility of shipping freight rates imposes one of the largest business risks for a shipping firm (for an overview of business risks in shipping see Kavussanos and Visvikis, 2006). This high volatility in shipping freight rates is mainly due to the unique characteristics of the shipping industry such as: the inelastic supply of transportation service, as ships take considerable time to be built; and the derived demand for the transportation service, as the original demand is primarily created for the cargo (commodity) transported, which in turn creates the demand for the transportation service.

[4] In fact, shipping freight rates provide an effective global economic activity indicator (Kilian, 2009) and their importance exceeds industry's boundaries, as they affect significantly the global capital markets (Alizadeh and Muradoglu, 2014; Apergis and Payne, 2013).