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The effects of geopolitical risk and economic policy uncertainty on dry bulk shipping freight rates

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Abstract

We examine the effects of geopolitical risk (GPR) and economic policy uncertainty (EPU) on shipping freight rates using a Bayesian VAR model. A positive shock to global GPR has an immediate positive, but gradually diminishing, effect on dry bulk shipping freight rates. This effect is driven by global rather than country-specific GPR shocks. Positive shocks to EPU indices for the U.S., Brazil, and China trigger a negative response of dry bulk shipping freight rates that builds gradually over several months. Historical cumulative effects of both GPR and EPU shocks on freight rates can be large and of different signs during different subperiods. Our results are important for both shipowners and charterers when fixing chartering strategies and prioritizing investments in newbuilding or second-hand vessels.

Keywords: Geopolitical risk; economic policy uncertainty; shipping freight rates; Bayesian VAR.

JEL classification: C1, D80, R40.

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Abstract

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1. Introduction

Shipping freight rates are linked tightly to the global real economic activity and the global demand for commodities (Kilian, 2009; Kilian and Zhou, 2018). As reported in Alexandridis et al. (2018), the commercial shipping industry facilitates between 80% and 90% of global commodity trade in volume terms and, by adding about $380 billion a year via freight rates alone to the global economy, contributes markedly to the welfare and development of nations. Given the shipping industry's truly global character (Stopford, 2009), we expect freight rates to be strongly affected by the forces of geopolitical risk (GPR) and economic policy uncertainty (EPU). Shocks to both GPR and EPU trigger a decrease in global industrial production (Caldara and Iacoviello, 2019; Baker et al., 2016) and lead to lower investment rates (Gulen and Ion, 2016). These negative economic effects will reduce the overall demand for sea transportation, and shipping firms' revenue sources are likely to be affected as well (albeit the effects of GPR and EPU on freight rates can be very different, as will be shown below).

Major geopolitical events in the past, such as the closure of the Suez Canal due to Egypt's war in 1967 and the Iraq-related oil crisis in 1990, had pronounced effects on the global shipping industry. Similarly, adverse events related to economic policy, such as financial and/or economic crises, trade wars with heavy tariffs, and quotas on imports and exports of leading trading nations, all negatively affect shipping markets. Recent examples include the Lehman Brothers default in 2008 and the resulting global financial crisis, as well as the tariffs imposed by the U.S. government on Chinese imports in 2018. All of these events negatively affected the global economy and, as a direct consequence, impaired the financial strength of commercial shipping firms. Put differently, the riskiness of operating in the shipping industry is at least partly attributable to GPR and EPU shocks, which ultimately affect the freight rates that vessels can earn on major routes.

There are additional reasons why the shipping industry is an ideal subject of research on the economic effects of GPR and EPU. For example, Caldara and Iacoviello (2019) find that exposure to GPR is larger for industries that are more cyclically-sensitive, that are more open to international trade, and where firms are more levered. The academic literature on shipping finance documents that the shipping industry resembles these characteristics; it is a volatile business (Albertijn et al., 2011), one that is tightly linked to global business cycles (Drobetz et al., 2016) and features very high financial leverage (Drobetz et al., 2013). Moreover, real options theory predicts a negative relation between uncertainty and investment, where firms facing high uncertainty optimally delay investments so that they can "wait and see" to avoid costly mistakes (Bernanke, 1983; Brennan and Schwartz, 1985; McDonald and Siegel, 1986). Investment decisions in the shipping industry, e.g., freight rate chartering contracts or investments in new or secondhand vessels, contain such an option-to-wait component. This implies that the economic effects EPU exerts should be particularly strong in the shipping industry.[1]

Despite their adverse economic effects overall, the two concepts of risk, GPR and EPU, can affect freight rates in different ways. First, an unexpected increase in GPR may translate into higher insurance fees, higher operational risks (including possible delays in journey times), and higher bunker consumption, if, for example, changes in routes become necessary. Ship owners may also face higher risks in fulfilling transportation that has been agreed to with charter parties subsequent to a GPR shock, and require higher freight rates, ceteris paribus. Therefore, we expect positive GPR shocks to increase freight rates (shipping firms' earnings).[2] Second, major economic

[1] In addition, the riskiness of operating in the shipping industry may be due to other factors, such as segmentation of shipping markets (Kavussanos, 1996; Tsouknidis, 2016) or poor corporate governance mechanisms (Andreou et al., 2014). For a comprehensive review of related shipping finance literature, see Alexandridis et al. (2018).

[2] In several instances throughout this paper, we refer to earnings and freight rates interchangeably, in order to make the analysis and discussion easier to follow.

policy events can induce higher market uncertainty and lower (delayed) investment activity, reducing the global demand for sea transportation of vital commodities for international trade, such as iron ore, coal, grain, and crude oil. Therefore, ceteris paribus, lower demand for sea transportation decreases freight rates.[3]

This straightforward economic rationale suggests important and direct relationships among geopolitical risk, economic policy uncertainty, and the global shipping freight markets. However, to the best of our knowledge, no empirical study has yet modelled and quantified these economic forces. Our paper attempts to fill this gap in the literature. The absence of empirical evidence may be attributable, among other factors, to the elusive nature of the concepts behind GPR and EPU. Caldara and Iacoviello (2019) and Baker et al. (2016) provide news-based global and country-specific indices of GPR and EPU, respectively, which we exploit in our empirical analysis. A unique property of these novel measures is that they can be interpreted, to some extent, as exogenous shocks to international trade and the global shipping industry.[4]

We further mitigate any concerns about the existence of possible endogenous relationships across the variables of interest by using a Bayesian Vector Autoregressive (BVAR) framework to model these relationships. Kilian and Lutkepohl (2017) show that Bayesian techniques may increase estimation accuracy when estimating a VAR model. This is because they are often estimated on relatively short-period samples that can lead to imprecise estimates.

Our empirical results confirm that the effects of positive shocks on EPU and GPR on shipping freight rates differ substantially. In particular, a positive shock on GPR has an immediate

[3] For an analysis of the interplay between supply, demand, and freight rates, see Stopford (2009).

[4] A study related to the shipping industry that uses the GPR index is Kotcharin and Maneenop (2020). They document that shipping firms increase their cash reserves after a GPR shock, possibly to protect against cash flow risks.

positive, but gradually diminishing, effect on dry bulk shipping freight rates. This effect is driven by increases in global, rather than country-specific, geopolitical risk. In contrast, positive shocks on EPU across U.S., Brazil, and China trigger a more sustained negative effect on dry bulk shipping freight rates that builds gradually. Overall, our results indicate that global geopolitical tensions increase freight rates for capesize and panamax vessels due to increased concerns about the safety and security of transporting the cargo, while an increase in policy uncertainty in some leading trading nations, such as the U.S., Brazil, and Australia, negatively affect freight rates.

Our findings are of great importance to professionals in the shipping and trading industry, because they provide further insights into how freight markets behave during major events. Given the positive but decaying freight rate effect, ship owners and charterers seem to be concerned about GPR shocks for a few months when setting their strategy of chartering vessels, but not over a long-run horizon or at a mere regional level. The evidence further suggests that news about policy uncertainty, due to its long-lasting impact on aggregate investment activity and the demand for shipping tonnage, also has a notable effect on freight rates, albeit the effects of EPU shocks are smaller in absolute magnitude compared with GPR shocks. Overall, adverse GPR and EPU events are of paramount importance for both ship owners and charterers when fixing their chartering strategies and prioritizing investments in newbuilding or secondhand vessels.

Our results are important for shipping markets and global trade. A large fraction of capesize vessels are employed globally, since they are primarily chartered on iron ore and coal trades across Brazil and Australia (exporter countries) as well as Asia and Europe (importing regions). Similarly, panamax vessels also operate globally; they are chartered primarily for the grain trade between the U.S. (exporter) and Asia (importer). Our findings suggest that GPR can increase freight rates for capsize and panama vessels due to increased concerns about the safety and security of transporting the cargo. Conversely, an increase of EPU in leading trading nations decreases dry bulk shipping freight rates. We further document that the historical cumulative effects of both GPR and EPU on shipping freight rates can be very large and of different signs during different subperiods.

The remainder of this paper is organized as follows. Section 2 outlines the dataset and the methodology we use to quantify the relationships of interest. The empirical results and implications for freight markets are discussed in Section 3. Section 4 provides a summary and conclusion.

2. Research Design

2.1 Geopolitical risk

The first variable of interest in our empirical analysis is the Geopolitical Risk Index (GPR index) constructed by Caldara and Iacoviello (2019). The authors define GPR as the risk emanating from tensions between states and countries, wars, and terrorism attacks that affect the normal and peaceful course of international relations. To construct the index, they use software-automated text searches on the archives of eleven leading newspapers: The Boston Globe, The Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, The Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post. The GPR index measures the frequency of articles related to geopolitical events and risks that are relevant for major companies, investors, and policy makers. It is normalized to average a value of 100 during the 2000-2009 period, i.e., an index value of 200 indicates that the mentions of rising geopolitical risk in that month were twice as frequent as during the 2000s.

Caldara and Iacoviello (2019) also provide two subcomponents: 1) the geopolitical acts index (GPA), and 2) the geopolitical threats (GPT) index. GPA refers to periods of elevated geopolitical risks due to the realization of adverse geopolitical events, while GPT captures geopolitical threats that are not yet contemporaneously associated with geopolitical events, such as tensions before wars or terrorist attacks. Moreover, the authors construct GPR indices for countries that are leaders in international trade (imports and exports), e.g., the U.S., China, and Brazil.[5]

Geopolitical risk has significant effects on various aspects of economic life. For example, Caldara and Iacoviello (2019) find that a higher level of the global GPR index exerts a significantly negative impact on real economic activity on a global scale. The effect is even more pronounced in developed economies. In addition, they document that a higher GPR index leads to negative stock market returns and higher capital flows from emerging toward developed economies. The index has also been used in several studies that confirm its impact on various economic outcomes, such as corporate investment (Dissanayake et al., 2019), stock market volatility (Bevilacqua et al., 2019), tourism demand (Tiwari et al., 2019), gold prices (Baur et al., 2018), and oil returns and volatility (Demirer et al., 2019).

2.2 Economic policy uncertainty

The second variable of interest in our empirical analysis is the U.S Economic Policy Uncertainty Index (EPU), constructed by Baker et al. (2016). Policy uncertainty is the part of overall economic uncertainty that is attributable to the political and regulatory system. The EPU index is also text search-based, and captures the volume of news articles that discuss economic policy uncertainty as a percentage of the total number of published articles in ten large newspapers: USA Today, The Miami Herald, The Chicago Tribune, The Washington Post, The Los Angeles Times, The Boston Globe, The San Francisco Chronicle, The Dallas Morning News, The New York

[5] Caldara and Iacoviello (2019) provide further detailed information about the construction of the GPR index and its subcomponents.

Times, and The Wall Street Journal. The index is normalized to an average of 100. In addition to the aggregate index, Baker et al. (2016) provide a series of indices for policy categories such as monetary, fiscal, trade, national security, and regulation.[6] The EPU index is also available for large trading countries like China and Brazil.

EPU has been shown to have a profound effect on a variety of macroeconomic variables, e.g., economic growth (Baker and Bloom, 2013), business cycles (Basu and Bundick, 2012), stock prices (Pastor and Veronesi, 2012), oil prices (Antonakakis et al. 2014), and tourism demand (Dragouni et al., 2016). At a firm level, the EPU index is related to capital expenditures (Gulen and Ion, 2016; Drobetz et al., 2018), research and development expenditures (Stein and Stone, 2014), mergers and acquisitions (Bonaime et al., 2018), leverage (Colak et al., 2018), equity issuance (Jens, 2017), and earnings management (Stein and Wang, 2016).

2.3 Data

We use monthly observations for the GPR and EPU global and country-specific indices, as well as earnings for capesize and panamax dry bulk vessel sizes.[7] Our sample period ranges from January 1991 through October 2018, resulting in 334 monthly observations.[8] This period covers several full cycles of the shipping industry, e.g., the “golden era” of 2003-2008 and the global financial crisis period of 2008-2012. Therefore, it is representative of both up and down periods.

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[6] Baker et al. (2016) provide further details about the construction of the EPU indices.

[7] GPR indices are available at: https://matteoiacoviello.com/gpr.htm (last accessed April 2020); EPU indices are available at: https://www.policyuncertainty.com (last accessed April 2020). As a robustness test, we replaced EPU-US with the global EPU index in our estimations, which, however, is available only from 1997 onward. Our results remain qualitatively the same due to this change, and are available from the authors upon request.

[8] The sample period begins at the earliest possible date when taking into account the availability of all variables.

In order to normalize freight rates across different vessel types, and thus enable comparisons across rates, our analysis includes monthly freight rates net of operational and voyage costs. These net rates reflect a vessel's effective earnings. Using earnings instead of freight rates excludes any effect on freight rates that may stem from a contemporaneous shock on bunker prices. Vessel-specific earnings time series are calculated and published by Clarksons Shipping Intelligence Network (SIN) across vessel sizes. In our analysis, we focus on the dry bulk capesize and panamax vessels, which transport basic construction, energy, and raw food commodities such as iron ore, coal, and grain (UNCTAD, 2019).[9]

We concentrate solely on the effects of the GPR and EPU indices on the freight rates of capesize and panamax vessels. In these shipping market segments, the shipping trade is relatively concentrated among specific countries.[10] The assumptions and standard vessel types used in the voyage earnings calculations are described in Clarksons (2013).[11] All variables used in our empirical model in Equation (1) below, along with their definitions and sources, are given in Table 1.

[9] Dry bulk cargo vessels are categorized by capacity as follows: capesize 100,000+ deadweight tonnage (dwt), panamax 60,000–100,000 dwt, handymax 40,000–60,000 dwt, and handysize 10,000–40,000 dwt.

[10] The dry bulk sector involves the transportation of homogeneous dry and wet bulk commodities – typically raw materials such as crude oil, iron ore, grains, coking and thermal coal, bauxite, and alumina, etc. – on non-scheduled routes on a one ship-one cargo basis. In 2019, dry bulk vessels carried more than 60% of the world's seaborne trade measured in ton-miles. Capesize vessels are used primarily in the trade of iron ore and coal commodities (UNCTAD, 2019). UNCTAD (2019) also cites the top importers of iron ore as China, Japan, South Korea, and Taiwan; the top exporters of coking coal as Australia, Canada, and the U.S.; and the top exporters of steam coal as Australia, Canada, Colombia, and Indonesia (World Coal Association). Therefore, the shipping trade routes among these countries are the major routes in the seaborne coal and iron ore trades. Similarly, panamax vessels have a large concentration of trade in the shipping route of the U.S. (the top exporter of grains) to Asian countries, such as China, India, and Japan, who are the top importers of grains. Since the GPR index is not available for Australia, we examine Brazil, the U.S., and China, which represent a sizeable part of the shipping trade conducted by capesize and panamax vessels.

[11] According to Clarksons (2013) ("Sources & Methods for the Shipping Intelligence Weekly"), daily net freight rates (earnings) for each route are computed as the net of total revenue minus the bunker costs based on prices at representative regional bunker ports, minus the port costs after currency adjustments and total commissions, divided by the number of voyage days. Details of these calculations and their constituent parameters and assumptions are in Annexes 1-4 of Clarksons (2013). For bulkers, average earnings for each ship type are averages of the voyage earnings for selected routes. The constituent routes are in Annex 4 (b) of Clarksons (2013).

Table 2 gives the descriptive statistics for all the variables. As expected, the average earnings and standard deviations are higher for the capesize than for the panamax vessels (Kavussanos, 1996). Positive skewness is present in all cases, and all series under investigation exhibit substantial excess kurtosis (above 3). In addition, all variables deviate significantly from the normal distribution, as indicated by the Jarque-Bera (1980) test statistic. We examine the stationarity of each time series by using the Augmented Dickey-Fuller (ADF, 1981) test, where the lag length of the ADF statistic is determined by minimizing the Schwarz (1978) Bayesian Information Criterion (SBIC). All time series are I(0) at the 10% significance level.

[Please insert Table 1 here]

[Please insert Table 2 here]

2.4 Methodology

In our analysis, we use a VAR model to examine the effects of GPR and EPU on shipping freight rates (SFR). Our VAR model is estimated through Bayesian techniques (BVAR). Kilian and Lutkepohl (2017) show that such techniques increase estimation accuracy because standard VAR models are often estimated on relatively short-period samples. This can lead to imprecise estimates. Therefore, shrinking parameter estimates toward benchmark values through Bayesian techniques helps to significantly reduce the variance of unrestricted least squares estimators.

More specifically, the Bayesian approach provides a formal framework for incorporating the extraneous information in estimation and inference. It also facilitates the inclusion of extraneous economic information about the VAR model parameters that would be difficult to incorporate into a standard VAR estimation. A BVAR in our estimation setting is advantageous because the sample period is relatively short compared with those in other macro-finance studies (Baumeister and Hamilton, 2019; and Kilian and Zhou, 2018).[12] Other recent studies also rely on a BVAR model when examining a relatively short time series (e.g., Auer, 2019).

The structural representation of the VAR model of order p is:

$$Y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + u_t \quad (1)$$

where $Y_t = (GPR_t, EPU_t, SFR_t)$ is a 3×1 vector of (possibly) endogenous variables, c represents a 3×1 vector of constants, A_i denotes the 3×3 autoregressive coefficient matrices, and u_t stands for the 3×1 vector of structural disturbances, assumed to be normally distributed. As discussed earlier, GPR is Caldara and Iacoviello's (2019) global geopolitical index, and EPU represents Baker et al.'s (2016) economic policy uncertainty index. SFR is the logarithm of real dry bulk shipping freight rates. GPR represents the time series GPR_GLOBAL, GPR_BRAZIL, and GPR_CHINA interchangeably, and the corresponding EPU time series similarly refer to EPU_US, EPU_BRAZIL, and EPU_CHINA.

Freight rates (earnings) are selected across capesize ($CAPE$) and panamax (PMX) vessels, using both voyage (spot) and one-year time charter (1YRTC) earnings. Specifically, we compute the log of real freight rates ($LRFR$) by deflating earnings as published by Clarksons SIN with the U.S. Consumer Price Index (CPI). In addition, we de-seasonalize freight rates (earnings) prior to inclusion in the VAR model, because they have been shown to exhibit pronounced seasonality (Kavussanos and Alizadeh, 2001).[13]

[12] In a robustness test, we also estimate the model in a standard VAR framework. The results are qualitatively similar and available from the authors upon request.

[13] Our results remain qualitatively the same if vessel earnings are not deflated or de-seasonalized.

Rewriting the VAR model in Equation (1) as a multivariate linear regression model yields:

$$Y = X\Phi + U \tag{2}$$

where $Y = (Y_1, Y_2, \ldots, Y_T)'$ is a $T \times n$ matrix, with T as the number of observed time periods; $X = (X_1, X_2, \ldots, X_T)'$ is a $T \times k$ matrix with $k = np + 1$; $\Phi = (A_1, A_2, \ldots, A_p, c)'$ is a $k \times n$ matrix containing all parameters; and $U = (u_1, u_2, \ldots, u_T)'$ is a $T \times n$ matrix of the error terms.

A Bayesian procedure treats the parameters as random variables and estimates them by imposing prior beliefs on their distribution. We follow Caldara and Iacoviello (2019) and impose a Normal-Wishart prior on the reduced-form VAR parameters, which is a modification of the Minnesota prior.[14] The structural shocks are identified using a Cholesky decomposition of the covariance matrix of the VAR reduced-form residuals in Equation (2). We choose to order the GPR index first as the most exogenous of the three variables used. This implies that the GPR index reacts contemporaneously only to its own shock. Accordingly, any contemporaneous correlations among the EPU index, shipping freight rates, and the GPR index will reflect the effect of the GPR index on these variables.[15]

[14] The Minnesota prior was originally developed by Litterman (1986) at the University of Minnesota and the Federal Reserve Bank of Minneapolis, and imposes a random walk representation for all variables. This seems to be a reasonable assumption for the prior for most macroeconomic variables, except those characterized by substantial mean reversion (Auer, 2019). However, shipping freight rates exhibit substantial mean reversion (Kyriakou et al., 2018). Moreover, the Minnesota prior imposes a fixed and diagonal covariance matrix of the residuals, which rules out possible correlations among residuals of different variables. Kadiyala and Karlsson (1997) and Robertson and Tallman (1999) suggest that a normal Wishart prior retains the principles of the Minnesota prior, but relaxes the assumptions on the covariance matrix structure of the residuals.

[15] In robustness tests, our estimates remain almost identical when we change the ordering of the variables in the BVAR model, i.e., the EPU index first and the GPR index second.

3. Empirical Results

3.*1* *Baseline results*

Figure 1 illustrates the median (blue solid lines) impulse response functions (IRFs) of freight rates (earnings) for each vessel type and charter agreement to a positive 1-standard deviation shock on GPR_GLOBAL, GPR_BRAZIL, and GPR_CHINA and on EPU_US, EPU_BRAZIL, and EPU_CHINA (i.e., an increase in geopolitical risk and policy uncertainty, respectively). The light blue shaded bands represent the 90% pointwise credible sets from the baseline model, and the horizontal axis shows the number of months since the shock.

[Please insert Figure 1 here]

Two main results emerge from Figure 1. First, a positive shock on GPR_GLOBAL triggers a statistically significant and immediate positive response, which dies away only gradually up to twenty months ahead of the shock across all freight rates examined (i.e., for capesize and panamax vessels, as well as for voyage (spot) and one-year time charter freight rates). This is apart from the spot freight rates of panamax vessels. In contrast, positive shocks on the GPR indices of Brazil and China trigger responses on all freight rates that are smaller in magnitude and weaker in terms of statistical significance.

Second, a positive shock on the EPU indices across all three countries (U.S., Brazil, and China) triggers a more sustained negative response, which builds gradually for up to twenty months ahead of the shock for all freight rates, i.e., capesize and panamax as well as voyage (spot) and one-year time charter freight rates. However, this response exhibits varying degrees of statistical significance: lower for the capesize spot freight rates, and higher for the rest of the cases examined.

Overall, the IRF results have important economic and managerial policy implications for players in the global shipping industry. On the one hand, positive unexpected changes in global GPR can increase freight rates in the capesize and panamax freight rate markets, but the effect is transient, dying away gradually (and fully up to twenty months from the shock). In contrast, the effect is not observable when GPR rises in countries such as Brazil and China, two of the leading import and export nations of dry bulk cargoes.

These results confirm our initial expectations that tensions between states and countries, wars, and terrorism attacks, which adversely affect international relations, will have a severe impact on dry bulk freight rates on a global scale. However, because the result is transient, and due only to global changes in GPR, rather than regional ones, it further reinforces the perception that the shipping industry is truly global in nature. This is because geopolitical events of different regional scales and magnitudes do not seem to systematically affect freight rates. In turn, we observe that ship owners and charterers are concerned about GPR events for a few months when setting their strategy of chartering vessels, but not over a long-run horizon or at a regional level.

On the other hand, as expected, positive shocks on EPU exert an economically large negative effect on dry bulk shipping freight rates. Events such as financial and economic crises, as well as trade wars that impose tariffs and quotas on imports/exports of leading trading nations, are truly global in nature. They lead to a longer-lasting decline in global demand for tonnage, and thus exert a more direct negative effect on shipping markets. Accordingly, news about market uncertainty is of paramount importance for both ship owners and charterers when fixing chartering strategies and prioritizing investments in newbuilding or secondhand vessels.

3.2 *Robustness tests*

In addition to the different specifications of the VAR model discussed in footnotes 11 and 12, we implement a series of other robustness tests to ensure our main results are not driven by the choice of the estimation method or the variables used. First, our findings remain qualitatively the same when we replace GPR with GPT (threats) or GPA (acts) (see Section 2.1 for a description). Second, we replace EPU_US with two subcomponent indices, national security (EPU_US_NS) and trade policy (EPU_US_TP), one at a time. In this case, shocks to EPU_US_NS and EPU_US_TP do not trigger significant effects on the freight rates of capesize or panamax vessels. Third, the results remain qualitatively unchanged when we use alternative numbers of draws (10K, 15K, 20K) and burning periods (1K, 2K, 3K, 4K observations) in the Normal-Wishart prior.

3.3 *Forecast error variance decomposition (FEVD)*

Figure 2 presents the forecast error variance decomposition (FEVD) for the estimated VAR model. FEVD shows the percentage of explained variance of freight rates attributed to shocks to the GPR and EPU indices. Similarly to the IRFs in Figure 1, we expand the forecast horizon from one month to twenty months ahead. In most cases, the effects of GPR_GLOBAL, GPR_BRAZIL, and GPR_CHINA can explain a high percentage of the variance of the freight rates examined (i.e., for capesize and panamax sizes as well as for voyage (spot) and one-year time charter freight rates). In sharp contrast, EPU_US, EPU_BRAZIL, and EPU_CHINA shocks cannot explain a considerable percentage of the variance of freight rates.

[Please insert Figure 2 here]

3.4 Historical decomposition

The impulse responses in Figure 1 assess the timing and magnitude of the responses of freight rates to one-time shocks of the GPR and EPU indices. However, the effects of historical episodes of GPR and EPU shocks on freight rates may not be limited to one-time shocks. Rather, they can involve a sequence of shocks, often coming with different signs at different points in time. To understand the cumulative effect of these historical sets of shocks, we perform a historical decomposition (HD) of freight rates. HD determines what portion of the deviation of a variable in the VAR model from its unconditional mean is due to the structural shock of another variable in the model.[16]

Figure 3 presents the HD performed here. To read it properly, we compare pairs of plots for GPR and EPU per region/country, i.e., the first pair is GPR_GLOBAL with EPU_US, the second is GPR_BRAZIL with EPU_BRAZIL, etc. For example, the first pair (GPR_GLOBAL and EPU_US) shows the contributions of global GPR shocks and U.S. EPU shocks to capesize spot freight rates at different points in time. As observed, GPR shocks strongly increase capesize spot rates during 2001 to 2003, and again after 2014 and up to 2018. In contrast, U.S. EPU shocks decrease capesize spot rates during 2000 to 2003, a period that coincides with the dot.com bubble in the U.S. stock market, and during 2008-2013, the period that covers the global financial crisis.

[Please insert Figure 3 here]

Taken together, the contributions of GPR shocks across all three regions (global, Brazil, and China) tend to decrease freight rates during 1991-2000, apart from the capesize 1YRTC. After

[16] Each observation of a variable does not generally coincide with its unconditional mean. This is because, in each period, the structural shocks realize and push all variables away from their equilibrium values.

2000, GPR shocks generate different contributions to freight rates. For example, GPR_BRAZIL exhibits limited contributions, while GPR_CHINA decreases panamax freight rates.

In contrast, the contributions of EPU shocks for each country are consistent across all freight rates examined. Specifically, U.S. EPU shocks tend to decrease the level of freight rates during 1991 to 1993 (the oil crisis), 2000 to 2003 (the dot.com crisis), and 2008 to 2013 (the global financial crisis); in contrast, they increase freight rates during other periods. EPU_BRAZIL increases freight rates during 1991 to 1999, but decreases them during 1999 to 2008. These effects are more severe for the capesize and panamax 1YRTC. Finally, EPU_CHINA increases freight rates strongly during 1999 to 2007. This period has two important characteristics, which have a marked influence on freight rates: 1) China enters the World Trade Organization (WTO) in 2001, and 2) there is no economic or financial crisis, apart from the severe 2001 dot.com bubble crisis.

From these findings, it becomes apparent that the effect of EPU_US on freight rates corresponds to a large extent to the state of the global economy and to growth in trade. This is expected, given that U.S. GDP growth is strongly linked with global GDP growth. Similarly, EPU_CHINA exhibits pronounced cumulative effects across all shipping freight rates. This pattern is similar to that of U.S. EPU effects and confirms China's great influence on the global shipping industry. The country exhibits a strongly increasing GDP, while simultaneously being one of the leading seaborne trading nations in the world.

In contrast, EPU_BRAZIL does not exert a large impact on global shipping freight rates when compared to EPU_US or EPU_CHINA. Despite its status as a leading exporter of iron ore and coal, which are primarily transported using capesize vessels, Brazil's GDP and economic growth lag those of the U.S. and China significantly.

Taken together, our results highlight several important facts. While one-time shocks trigger, on average, positive (GPR) or negative (EPU) responses of shipping freight rates (see Figure 1), the historical cumulative effects on shipping freight rates can be very large and of different signs during different subperiods (see Figure 3). These periods of interest can be linked consistently to developments in the global economy and shipping cycles.

4. Conclusion

This study contributes to the literature by quantifying the effects of geopolitical risk and economic policy uncertainty on shipping freight rates, a key indicator variable of global trade (Kilian, 2009; Kilian and Zhou, 2018). We use a well-developed and robust Bayesian VAR framework that increases the accuracy of our inferences. Our results reveal that the effects of positive shocks on EPU and GPR on shipping freight rates can differ dramatically. A positive shock on global GPR has an immediate positive but gradually decreasing effect on shipping freight rates. This effect is driven by global rather than by country-specific GPR increases. In contrast, positive shocks on EPU for the U.S., Brazil, and China trigger a more sustained negative effect on shipping freight, which build gradually. Overall, these findings have important economic and managerial policy implications for players in the global shipping industry.

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Table 1: List of variables

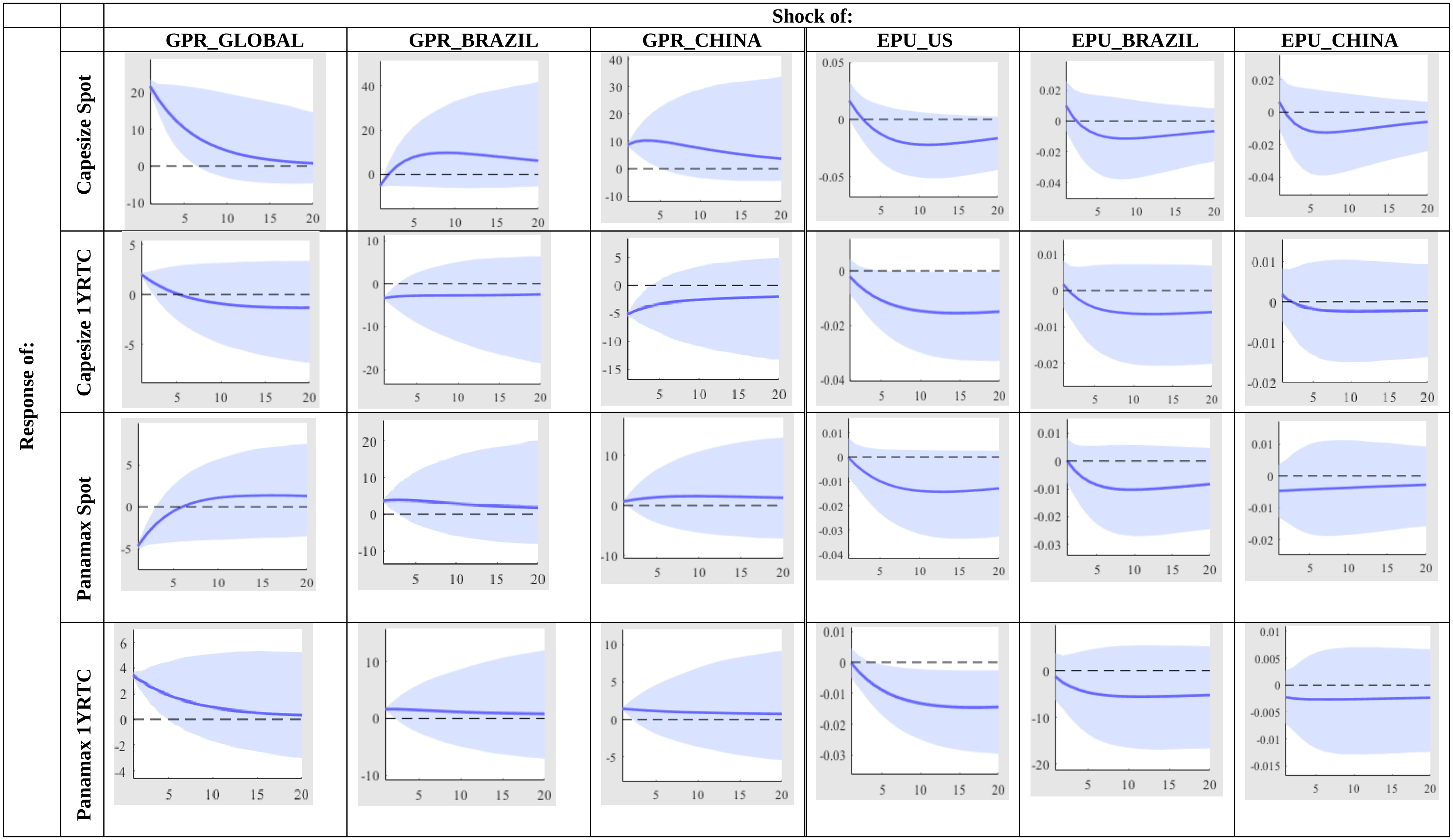
Symbol	Description	Source
GPR_GLOBAL GPR_CHINA GPR_BRAZIL	A global index of geopolitical risk, defined as risk from tensions between states and countries, wars, and terrorism attacks, that affect the normal and peaceful course of international relations. The GPR index is constructed using software-automated text searches on the archives of eleven leading newspapers. GPR indices are available for several countries, such as China and Brazil. For details, see Caldara and Iacoviello (2019).	Website of Matteo Iacoviello: https://matteoiacoviello.com/gpr.htm
EPU_US EPU_BRAZIL EPU_CHINA	The EPU index is text search-based and captures the volume of news articles that discuss economic policy uncertainty as a percentage of the total number of published articles in ten large newspapers. For details, see Baker et al. (2016).	Website of Baker et al. (2016): https://www.policyuncertainty.com/
LRFR_SPOT_CAPE ($/day) LRFR_1YRTC_CAPE ($/day) LRFR_SPOT_PMX ($/day) LRFR_1YRTC_PMX ($/day)	These vessel-specific earnings time series are calculated and published by Clarksons Shipping Intelligence Network (SIN) across vessel sizes. According to Clarksons (2013) ("Sources & Methods for the Shipping Intelligence Weekly), daily net freight rates (earnings) for each route are computed as the net of total revenue minus the bunker costs based on prices at representative regional bunker ports, minus port costs after currency adjustments and total commissions, divided by the number of voyage days. We compute the natural loarithm of real freight rates (LRFR) for two types of chartering contracts for a vessel (SPOT and one-year time charter 1YRTC) and for two types of vessels (capesize, CAPE, and panamax, PMX).	Clarksons Shipping Intelligence Network (SIN)

Table 2: Descriptive statistics

	Mean	Median	Standard deviation	Min.	Max.	Skewness	Kurtosis	J-B [p-value]	ADF [p-value]
GPR_GLOBAL (index units)	83.57	63.20	64.24	23.70	545.09	3.20	18.26	3,946.58 [0.0000]	-5.29 [0.0000]
GPR_CHINA (index units)	104.49	98.38	25.79	61.94	206.69	1.33	4.91	156.05 [0.0000]	-6.28 [0.0000]
GPR_BRAZIL (index units)	99.51	96.72	28.08	43.05	228.54	1.19	5.96	209.40 [0.0000]	-7.20 [0.0000]
EPU_US (index units)	107.02	99.51	32.81	57.20	245.13	1.02	3.79	69.76 [0.0000]	-3.38 [0.0123]
EPU_BRAZIL (index units)	127.05	107.47	86.61	12.68	676.95	2.27	10.76	1,127.03 [0.0000]	-4.13 [0.0010]
EPU_CHINA (index units)	105.99	95.79	66.10	0.00	395.67	1.49	5.78	233.11 [0.0000]	-3.24 [0.0156]
LRFR_SPOT_CAPE ($/day)	27,135.60	16,632.98	30,080.25	1,071.33	188,643.40	2.68	11.13	1,367.86 [0.0000]	-2.55 [0.0986]
LRFR_1YRTC_CAPE ($/day)	27,097.23	16,468.75	28,887.23	6,131.25	161,600.00	2.99	12.37	1,783.90 [0.0000]	-3.03 [0.0328]
LRFR_SPOT_PMX ($/day)	14,500.92	10,301.94	12,402.90	4,159.60	74,099.01	2.60	10.11	1,118.86 [0.0000]	-3.33 [0.0139]
LRFR_1YRTC_PMX ($/day)	16,035.69	11,146.88	13,724.39	5,062.50	79,375.00	2.85	11.51	1,511.42 [0.0000]	-3.11 [0.0266]

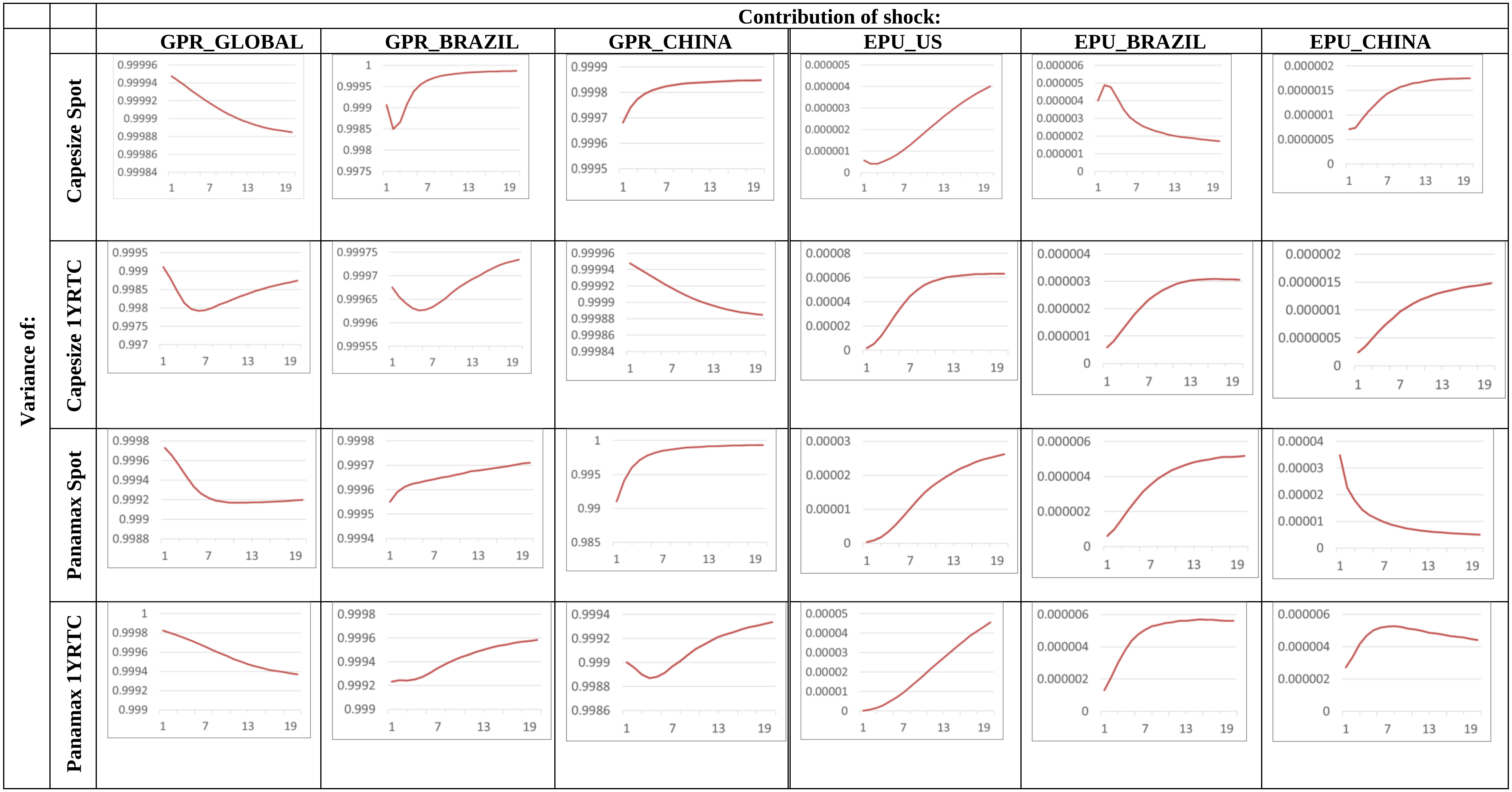
Notes: This table shows descriptive statistics for the sample period 1991:01 to 2018:10. GPR is Caldara and Iacoviello's (2019) global geopolitical index, and EPU represents Baker et al.'s (2016) economic policy uncertainty index. Freight rates (earnings) are for capesize (CAPE) and panamax (PMX) vessels, using both voyage (spot) and one-year time charter (1YRTC) earnings. For example, *LRFR_SPOT_CAPE* stands for the logarithm of real freight rates (LRFR) for spot freight agreements and for capesize vessels. The rest of the variables follow the same notation. Min. and Max. are the minimum and maximum values of the sample data, respectively. Skewness and kurtosis are the estimated centralized third and fourth moments of the data. J-B is the Jarque and Bera (1980) test for normality; the statistic is χ^2 distributed. ADF is the Augmented (Dickey and Fuller, 1981) stationarity test. The ADF regressions include an intercept term. The lag length of the ADF test is determined by minimizing the Schwarz (1978) Bayesian Information Criterion (SBIC). Numbers in square brackets [.] indicate p-values.

Figure 1: Impulse response functions



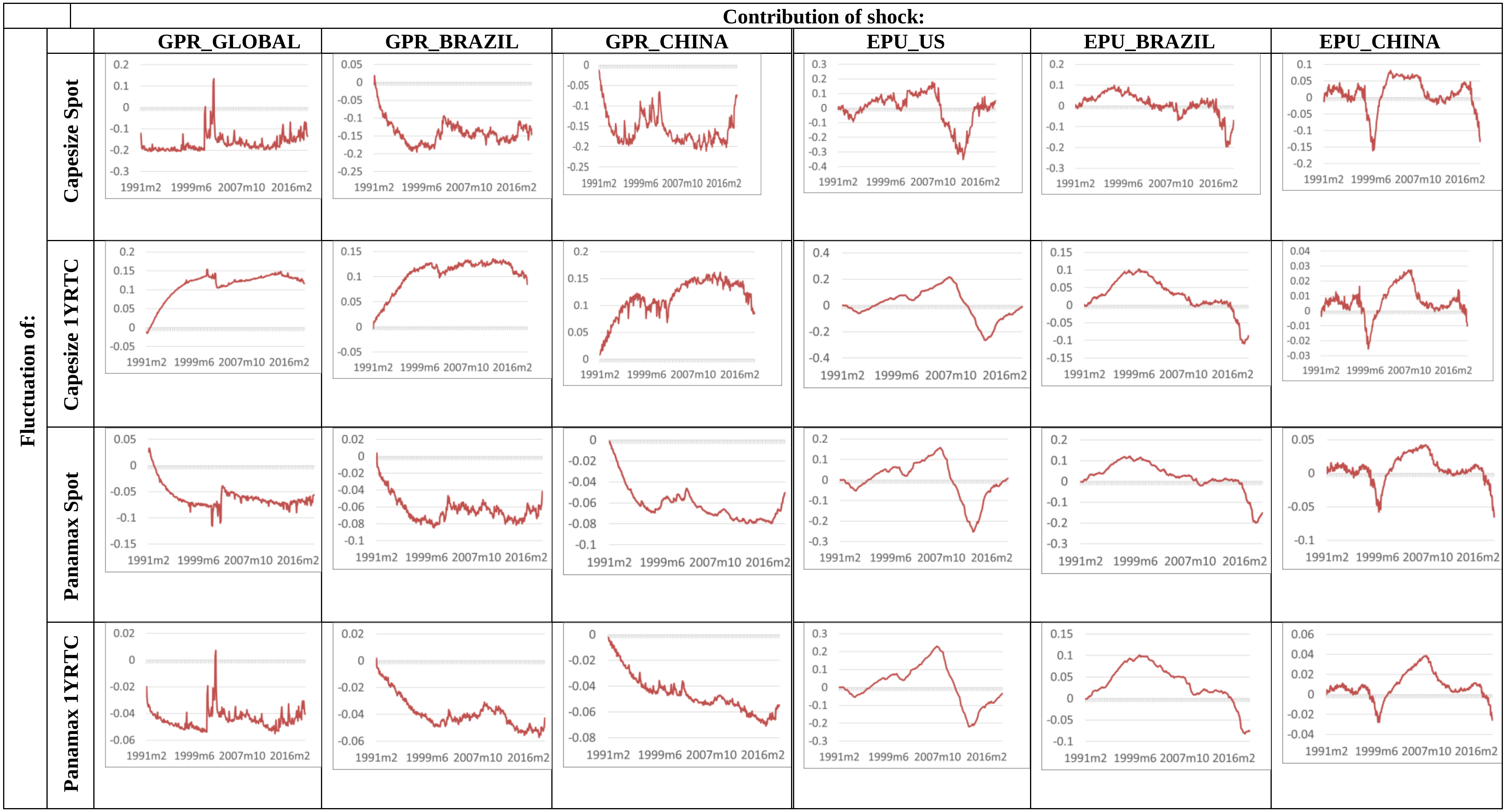
Notes: This figure shows impulse response functions of the log of real de-seasonalized freight rates to a positive shock of GPR_GLOBAL, GPR_BRAZIL, GPR_CHINA (left panel), and EPU_US, EPU_BRAZIL, EPU_CHINA (right panel). Freight rates (earnings) are for capesize (CAPE) and panamax (PMX) vessels, using both voyage (spot) and one-year time charter (1YRTC) earnings. The blue solid line shows the median impulse response of each variable (rows) to a positive shock equal to 1-standard deviation of each variable (columns) in the baseline BVAR specification. The shaded bands represent 90% pointwise credible sets from the baseline model, respectively. The horizontal axis shows the number of months since the shock.

Figure 2: Forecast error variance decompositions



Notes: This figure shows the forecast error variance decompositions (FEVD) of the log of real de-seasonalized freight rates to a positive shock of GPR_GLOBAL, GPR_BRAZIL, GPR_CHINA (left panel), and EPU_US, EPU_BRAZIL, EPU_CHINA (right panel). Freight rates (earnings) are for capesize (CAPE) and panamax (PMX) vessels, using both voyage (spot) and one-year time charter (1YRTC) earnings. The red solid line shows the median percentage of the variance of shipping freight rates that can be explained by a positive shock on EPU and GPR. These estimates are based on the forecast error variance decomposition (FEVD) of the three-variate VAR model in Equation (1). The horizontal axis shows the number of months since the shock.

Figure 3: Historical decompositions



Notes: This figure shows historical decompositions (HD) of the log of real deseasonalized freight rates to a positive shock of GPR_GLOBAL, GPR_BRAZIL, GPR_CHINA (left panel), and EPU_US, EPU_BRAZIL, EPU_CHINA (right panel). Freight rates (earnings) are for capesize (CAPE) and panamax (PMX) vessels, using both voyage (spot) and one-year time charter (1YRTC) earnings. The red solid line in each panel depicts the historical decomposition (HD) for each three-variate VAR model in Equation (1). HVD shows the contribution of a positive shock on GPR and EPU on the variance (fluctuations) of shipping freight rates over the examined period 1991:01-2018:10.