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Supply Bottlenecks and Machine Learning Forecasting of International Stock Market Volatility

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Abstract

The objective of this paper is to forecast volatilities of the stock returns of China, France, Germany, Italy, Spain, the United Kingdom (UK), and the United States (US) over the daily period of January 2010 to February 2025 by utilizing the information content of newspapers articles-based indexes of supply bottlenecks. We measure volatility by employing the interquantile range, estimated via an asymmetric slope autoregressive quantile regression fitted on stock returns to derive the conditional quantiles. In the process, we are also able to obtain estimates of skewness, kurtosis, lower- and upper-tail risks, and incorporate them into our linear predictive model, alongside leverage. Based on the shrinkage estimation using the Lasso estimator to control for overparameterization, we find that the model with moments outperform the benchmark model that includes both own- and cross-country volatilities, but the performance of the former, is improved further when we incorporate the role of the metrics of supply constraints for all the 7 countries simultaneously. These findings carry significant implications for investors.

Keywords: Supply Bottlenecks; Stock Market Volatility; Asymmetric Autoregressive Quantile Regression; Lasso Estimator; Forecasting

JEL Codes: C22; C53; E23; G15

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1. Introduction

In the wake of the COVID-19 pandemic, which resulted in severe supply disruptions, a recent line of research has depicted that the effect of supply chain bottlenecks goes beyond the macroeconomic impacts of higher inflation and lower output (Diaz et al., 2023; Asadollah et al., 2024; Ascari et al., 2024; Tillmann, 2024, Ginn and Saadaoui, 2025a), and adversely impacts financial market performance in terms of decline in equity prices and leverage (see, for example, Hupka (2022), Smirnyagin and Tsyvinski (2022), Burriel et al. (2024), Ginn (2024) and Ginn and Saadaoui (2025b)).[1]

We aim to add to this strand of research on financial markets, by analysing the ability of the recently developed, by Burriel et al. (2024), daily newspaper articles-based supply bottlenecks indexes (SBIs) in forecasting stock market volatilities of China, France, Germany, Italy, Spain, the United Kingdom (UK), and the United States (US), over the period of January 2010 to February 2025.

In this regard, we analyze the role of own, as well as, cross-country or SBIs, while accounting for spillover of not only volatility across these equity markets, but also their associated moments, i.e., leverage, skewness, kurtosis, lower and upper tail risks, as highlighted by Foglia et al. (2025a, b). Note that, recent studies (see, for example, Mei et al. (2017), Zhang et al. (2021), Bonato et al. (2022, 2023)) have highlighted the importance of moments in predicting stock returns volatility equally well or even better than traditional predictors, since these price-based factors inherently incorporate information about extreme movements of macroeconomic and financial variables, reflecting investor sentiment and uncertainties.

To econometrically conduct our analysis, we firstly employ the asymmetric slope autoregressive quantile regression model of Engle and Manganelli (2004) on the stock returns to obtain a robust estimate of the corresponding volatility as an inter-quantile range from the conditional quantiles of the univariate framework. A further advantage of this approach is that we are also able to compute, from the estimated conditional quantiles, the abovementioned additional stock market moments such as, skewness, kurtosis, lower- and upper-tail risks, which, along with leverage (i.e., negative only stock returns), serve as our control variables. Then secondly, we utilized a linear predictive regression for volatility, but estimated using the popular least absolute shrinkage and selection operator (Lasso) estimator of Tibshirani (1996), given that our forecasting models, over rolling-windows of 250 days (i.e., 1 year), can contain between 22 to 64 predictors, associated with own- and cross-country lags of volatility, moments, and SBIs.

At this stage, it is important to discuss the theoretical channel that can be used to hypothesize the causal relationship from supply bottlenecks to stock market volatility of our analysis by realizing that the SBI resulting from not only strikes and price controls but also geopolitical risks, natural (climate-related) disasters, pandemics, and even trade wars, tend to act as a "catch-all" empirical proxy for rare disasters (Caldara et al., 2025; Polat et al., 2025). Given this, we derive our empirical predictive link from SBI to stock returns volatility based on the studies of Wachter (2013) and Tsai and Wachter (2015). These two papers develop theoretical models in which aggregate consumption in general follows a low-volatility normal distribution, but there exists a positive probability of events that cause, so-called, far-out-in-the-left-tail realizations of consumption and output. To put differently, these models capture the risk associated with rare disaster events. The possibility of such an extreme outcome not only

[1] In this regard, these papers can be considered to be building on the works of Hendricks and Singhal (2003, 2005a, b) and Baghersad and Zobel (2021), who using pre-COVID-19 data associated supply chain constraints with movements in shareholder value, equity risk and value, revenue, operating income, and returns on sales.

substantially reduces stock returns and raises the equity premium, but also produces high stock-market volatility due to the time-variation in the probability of such a disaster. Besides, with SBIs known to negatively influence macroeconomic variables in the form of higher inflation and lower output, which, in turn, considered to be important state variables for asset prices (Schwert, 1989), would convey "bad news" for financial markets, and is likely to increase the risk profile of equities and hence, raise its volatility (Engle et al., 2013).[2]

Given that the volatility of stock returns serve as a key input for portfolio and hedging decisions, and that accurate forecasts are critical for the effectiveness of portfolio and risk management strategies as well as the pricing of derivative securities (Rapach et al., 2008), such an empirical exercise should be of pertinent importance to investors, beyond its academic value. To the best of our knowledge, this is the first to analyze the forecasting ability of SBIs for international stock returns volatility using a (linear) machine learning approach. In the process, our paper can be considered to be an out-of-sample extension of the work of Bouri et al. (2025), who provide evidence of in-sample predictability for the conditional distribution of (returns and) volatility of these 7 stock markets, using a bivariate causality-in-quantiles-based model. But as is quite well-discussed (see, for example, Rapach and Zhou (2022), Goyal et al. (2024)) in-sample predictability of stock price movements does not necessarily translate into out-of-sample forecasting gains, with the latter being a relatively more robust test of predictability. In light of this, we add to the enormous strand of literature that offers a wide-array of linear and nonlinear models in univariate and multivariate settings to model and forecast international stock market volatility (see, Poon and Granger (2003), Corsi et al. (2012), Bhowmik and Wang (2020), Dhingra et al. (2024) for detailed reviews).

In order to get to our empirical findings, we organize the rest of the paper as follows. In Section 2, we provide a description of the data that we use in our study, while we outline our methodology and empirical results in Section 3, and then conclude in Section 4.

2. Data

We use the daily SBI, developed by Burriel et al. (2024), for China, France, Germany, Italy, Spain, the UK and the US, as our main predictor variable.[3] To develop the SBI index, Burriel et al. (2024) rely on counting the relative frequency of the number of newspaper articles belonging to two groups. The first one involves the topic of supply chains (such as "supply chain, supply chains, supply, supplies"), while the second group includes terms reflecting a negative tone or the existence of problems or disruptions (such as "bottleneck, bottlenecks, shortage, shortages, woe, woes, disruption, disruptions, problem, problems, scarcity, scarcities, lack, delay, delays, backlog, backlogs"). For the article to be identified as reflecting supply

[2] Using quantile regressions-based analyses, Ullah et al. (2025) have depicted a negative effect of supply constraints (captured by the Global Supply Chain Pressure Index (GSCPI) of Benigno et al. (2022)) on sentiments, which, in turn, from a behavioural perspective, is also known to increase stock market volatility (Gupta et al., 2023). Regressing the first principal component of metrics of sentiments, as created by Ahir et al. (2022), derived from monthly data for 71 countries over 2008:01 to 2025:05, and quarterly data for 143 economies covering 1998:01 to 2025:01, we found a negative and statistically significant relationship from the GSCPI primarily at lower and, to some extent upper quantiles of the monthly and quarterly factors. Specifically speaking for the former, the t-statistics were -2.19961, -3.2609, -3.1364, and -1.8306 for quantiles 0.10, 0.15, 0.20 and 0.95, respectively, and for the latter the same were -3.4174, -3.4426, -1.7874, and -1.8050 at quantiles 0.05, 0.10, 0.15 and 0.80, respectively. The relationship was, however, negative over the entire conditional distributions of the monthly and quarterly factors. Complete details of these results are available upon request from the authors. Note that, the GSCPI can be downloaded from: https://www.newyorkfed.org/research/policy/gscpi, while the sentiment data is available at: https://worlduncertaintyindex.com/data/.

[3] The SBIs are available for download from: https://www.bde.es/wbe/en/areas-actuacion/analisis-e-investigacion/recursos/indices-de-cuellos-de-botella-en-la-oferta-basados-en-articulos-de-prensa.html.

chain-related concerns, a word from each one of the two groups must be present within a range of 10 words.[4] In the process, the SBIs offer a unique and timely (real-time) way of measuring supply chain disruptions from media sources.

We also use the corresponding daily stock indexes, i.e., the SHCOMP, the CAC 40, the DAX, the FTSEMIB, the IBEX 35, the FTSE 100, and the S&P 500 for China, France, Germany, Italy, Spain, the UK and the US, respectively, with these indexes obtained from the Bloomberg terminal. After we compute the log-returns of the stock market indexes, they are subsequently fitted to the autoregressive quantile regression of Engle and Manganelli (2004), given by: $Q^p(y_t) = \beta_0^p + \beta_1^p(y_{t-1}) + \beta_2^p y_{t-1}\Pi(y_{t-1} > 0) + \beta_3^p y_{t-1}\Pi(y_{t-1} < 0)$. This asymmetric slope model allows for a different, but persistent, impact of past observations on the respective quantiles, depending on whether they lie above or below the unconditional mean of the series. This permits an asymmetric impact of contractions and expansions in stock returns on the different quantiles, such that a bearish (bullish) market can affect downside (upside) risk without necessarily affecting upside (downside) risk. Once we obtain the fitted values of stock log-returns ($\widehat{Q_t^p}$) for each of the 7 countries at the conditional quantiles, i.e., p = 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, and 0.99, we, along with leverage (LEV) — a time series involving the days that correspond to only negative raw (i.e., unfitted) stock log-returns, obtain our estimates of lower (LTR)- and upper (UTR)-tail risks, skewness (SKEW) and kurtosis (KURT), to forecast our metric of oil log-returns volatility, namely the inter-quantile range (IQR). In line with Gupta et al. (2023), note that, IQR = $\widehat{Q_t^{0.90}} - \widehat{Q_t^{0.10}}$; LTR = $\widehat{Q_t^{0.05}}$; UTR = $\widehat{Q_t^{0.95}}$; SKEW= $(\widehat{Q_t^{0.90}} + \widehat{Q_t^{0.10}} - 2\widehat{Q_t^{0.50}})/(\widehat{Q_t^{0.90}} - \widehat{Q_t^{0.10}})$, and; KURT = $(\widehat{Q_t^{0.99}} - \widehat{Q_t^{0.01}})/(\widehat{Q_t^{0.75}} - \widehat{Q_t^{0.25}})$.

Given the common starting point of the SBI indexes, our analysis spans the period of 15th January 2010 to 28th February 2025, with the untransformed SBIs used as predictors, over and above the stock market moments.

3. Forecasting Model and Results

Our predictive regression model is specified as follows:

$$IQR_{t+h} = c + Z_t'\gamma + \epsilon_{t+h} \tag{1}$$

where h denotes the forecast horizon (in months); IQR_{t+h} denotes the average of volatility between periods of time t and $t + h$, with volatility being captured by the inter-quantile range (IQR) obtained from the estimated quantiles of the asymmetric slope autoregressive quantile regression; Z_t is the vector of our predictors, which vary according to the models under consideration, and are described below; ϵ_{t+h} denotes the usual disturbance term, and; c denote the constant, i.e., the conditional mean of IQR_{t+h}, and; γ is a vector of coefficients in $\boldsymbol{R^n}$, corresponding to Z_t involving n predictors, that needs to be estimated.

As far as our benchmark model (M1) is concerned, X_t includes 3 lags of IQR_t of each of the 7 stock markets, chosen based on the Akaike Information Criterion (AIC), to account for volatility interconnectedness. Model 2 (M2) builds on M1 by including LEV, SKEW, KURT, LTR and UTR of not only the particular stock market volatility that we are forecasting, but also

[4] In the case of the European countries, Burriel et al. (2024) relied on native speakers to translate the words to national languages, while the index for China is based on news from international and domestic sources that are in English.

those of the remaining 6. Model 3 (M3) add own-country SBI to the predictors in M2, while M4 extends the covariate set of M3 by including the other-country SBIs.

Given the above set-up, M1, M2, M3, and M4 contain 22, 57, 58 and 64 predictors, and with us using a rolling-window prediction structure involving 250 daily observation each time, we use the popular Lasso shrinkage estimator to accommodate for the possibility of overparameterization and associated poor out-of-sample forecasting performance. The idea underlying this shrinkage estimator is to reduce the dimension of a regression model in a data-driven manner to improve the accuracy of predictions derived from the penalized model as follows:

$$\widehat{\gamma_{Lasso}} = argmin \left(\sum_{t=1}^{T} (IQR_{t+h} - c - Z_t'\gamma)^2 \; + \; \lambda \sum_{j=1}^{n} |\gamma_j|\right) \tag{2}$$

where T denotes the number of observations used to estimate the forecasting model; λ is a shrinkage parameter, and; n corresponds to the number of coefficients that are subject to the shrinkage process. Hence, the Lasso estimator adds to the standard quadratic loss function in ordinary least squares (OLS) estimator a penalty term that increases in the absolute value of the coefficients. The Lasso estimator, thereby, shrinks a few co-ordinates towards zero, where the effect of this shrinking must be balanced against the resulting effect on the quadratic loss function. The final non-zero coefficients indicate the corresponding predictors are significant.

As far as our forecasting set-up is concerned, we use the first 1 year as our in-sample, and then roll this window of 250 days forward by leaving out one initial observation till 28/02/2025-h to produce h =1-, 5-, 22-, 44-, and 66-day-ahead forecasts. Note that, to prevent any possibility of a look-ahead-bias in the derived values of SKEW, KURT, LTR and UTR, the asymmetric slope autoregressive quantile regression was re-estimated across the various quantiles using a rolling-window of 250 days as well.

As a matter of completeness, Table A1 in the Appendix of the paper presents the Root Mean Square Errors (RMSEs) of model M1, as well as the RMSEs of M2, M3 and M4 relative to M1; M3 and M4 relative to M2, and; M4 relative to M3. However, to get a clear inference from our forecasting results, given the similar-sized RMSEs of M2, M3 and M4, we focus on the Clark and West (2007; CW) test of statistical significance of forecasts involving two nested competing models, as is the case with our model specifications. Recall that the number of predictors (specified in brackets) are increasing as we move from M1 (22) to M2 (57), M2 (57) to M3 (58), and M3 (58) to M4 (64). The null hypothesis posits that both models exhibit equal predictive performance, whereas the alternative hypothesis suggests that the competing (unrestricted larger) model outperforms the restricted smaller model. Hence, the CW test is a one-sided test, with the p-values reported in Table 1 for M2, M3 and M4 versus M1; M3 and M4 versus M2, and; M4 versus M3.

[INSERT TABLE 1]

As can be seen from Table 1, M2, M3 and M4, with the exception of M2 and M3 for the US at h = 66, consistently outperforms the benchmark M1 containing lagged volatilities of all the 7 equity markets at the 1% level of significance for each of the five forecast horizons considered. This suggests the importance of not only (own and cross-country) moments in forecasting international stock market volatility in line with the existing literature (as in, for example, Mei et al. (2017), Zhang et al. (2021), Bonato et al. (2022, 2023)), but also that the added information of own and other-country SBIs plays pertinent roles in this context as well. While the forecasting models with SBIs tend to outperform the benchmark which contains only lagged information of volatility, an important question at this stage is whether M3 outperforms M2 or not in a statistically significant manner, i.e., whether own supply bottlenecks contain additional information over the moments of the seven countries considered simultaneously in forecasting individual stock returns volatility. The *p*-values of the CW test statistics, indicate that out of the maximum possible 35 cases, in 21 instances (60% of times),[5] particularly at medium- to long-run, M3 fails to outperform M2. In other words, own- and cross-country moments tend to perform better than economy-specific SBIs in forecasting stock market IQR. However, when we also consider the role of other country SBIs in the model, i.e., M4, the performance improves drastically, with this model outperforming M2 in 27 out of the 35 cases,[6] i.e., in 77% of the instances. Clearly, other country SBIs, given an interconnected supply chain system of the global economy, reflecting global disaster risks, is of significant importance, from a statistical sense, in forecasting stock returns volatility of the 7 economies considered.[7] Not surprisingly, in 30 out of 35 cases (i.e., 86% of times), where M4 outperforms M3.[8]

In sum, the information content of supply bottlenecks in forecasting the future path of stock market volatilities of China, France, Germany, Italy, Spain, the UK and the US matter over lagged volatilities and moments of these 7 markets considered simultaneously, but primarily when, we include cross-country SBIs in addition to its own values of the same in the forecasting set-up.[9] In the process, to obtain reliable predictive inferences, we justify the need for out-of-sample forecasting, and hence, go beyond the bivariate in-sample analyses conducted by Bouri et al. (2025), who depicted consistent statistical importance of own-country SBIs in causing stock market volatility of these economies.

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[5] Specifically, these cases are: for China at $h = 5$; for France at $h = 22$, 44, and 66; for Germany at $h = 5$, 22, 44, and 66; for Italy at $h = 1$, 5, 22, 44, and 66; for Spain at $h = 66$; for the UK at $h = 22$, 44, and 66, and; for the US at $h = 5$, 22, 44, and 66.

[6] The 8 cases where M4 fails to perform better than M2 are: for China at $h = 5$; for France at $h = 66$; for Germany at $h = 5$, 44, and 66; for Spain at $h = 22$, and 44; for the UK at $h = 44$, and; for the US at $h = 44$.

[7] In a recent (working) paper Bonato et al. (2024) has highlighted the role of supply constraints (shortages) in forecasting equity returns volatility relative to moments for historical monthly data spanning 1900 to 2024. Given this, we revisited their findings using the same specifications outlined in M1, M2, M3 and M4 described above, with models now including information on the predictors for not only the US, but also Canada, France, Germany, Japan, and the UK. Note that, choice of these other countries is driven by the availability of newspapers-based indexes of shortages, as developed by Caldara et al. (2025), over January 1900 to December 2024, available for download from: https://www.matteoiacoviello.com/shortages.html. The corresponding stock indexes (namely, S&P/TSX-300, CAC-All Tradable, CDAX,, TOPIX, FTSE All Share, S&P 500 for Canada, France, Germany, Japan, the UK and the US) are obtained from Global Financial Database of Finaeon As can be seen from the *p*-values of the CW test statistics reported in Table A2 in the Appendix, based on a 120-month rolling window for $h = 1$, 3, 6, 12 and 24, we not only confirm the findings of Bonato et al. (2024), but, consistent with our daily findings, also depict the statistical importance of cross-country shortages in forecasting the IQR of the US stock market. In addition, own shortages only are found to be relevant for Canada and France, while for Japan, results are along the lines of the US, but weaker.

[8] The five cases where M4 does not outperform M3 are: for China at $h = 66$; for Spain at $h = 5$, 22, and 44, and; for the UK at $h = 44$.

[9] Based on the *p*-values of the CW test statistics reported in Table A3 in the Appendix again with a 250 days rolling-window estimation, a similar story (barring at $h = 44$ and 66 for China) emerges, when instead of France, Germany, Italy and Spain individually, we consider overall Europe. In this regard, our results are based on the same variables and models of the IQR considered for the 7 countries now for the 4 economies and/or regions: China, Europe, the UK, and the US. We use of the Euro Stoxx 50 stock index for overall Europe and the SBI for the European Monetary Union (EMU) in our models, with the data derived from the same sources mentioned in the data segment. Note that, the SBI of the EMU is the average value of the same for France, Germany, Italy and Spain.

4. Conclusion

We forecast volatilities of the stock returns of China, France, Germany, Italy, Spain, the UK, and the US over the daily period of January 2010 to February 2025 by utilizing the information content of newspapers articles-based indexes of supply bottlenecks. We measure volatility by employing the interquantile range, estimated through an asymmetric slope autoregressive quantile regression of stock returns to derive the underlying fitted quantiles. This approach also allows us to derive estimates of skewness, kurtosis, lower- and upper-tail risks, and incorporate them into our linear predictive model, alongside leverage. Based on the shrinkage estimation using the Lasso estimator to control for overparameterization, we find that the model with moments outperform the benchmark model that includes both own- and cross-country volatilities, but the performance of the former, is improved further when we incorporate the role of the metrics of supply constraints for all the 7 countries simultaneously.

Given that forecasts of volatility are used as inputs for optimal asset-allocation decisions, our findings suggest that incorporating the information content of own, and in particular, cross-country supply bottlenecks, over and above realized moments, in predictive models of volatility of 7 stock markets can help an investor to improve the design of portfolios across various investment horizons.

As part of further research, it would be interesting to extend our analysis to a broader set of stock markets to generalize our findings. However, as a first step in this direction, such an exercise might involve the creation of the corresponding SBIs of these additional economies. Moreover, given that, rare disaster risks have been associated with first- and second-moment movements in the prices of other asset classes (Gupta et al., 2019a, b), future research can be pursued in relating supply constraints with overall financial stress of a set of developed and developing countries.[10]

[10] Preliminary causality analysis involving a time series obtained from the cross-sectional maximums of Financial Stress Indexes (FSIs) for 110 countries, developed by Ahir et al. (2023), over the quarterly period of 1967:01-2023:04, with the global shortages index of Caldara et al. (2025), indicated that the latter tends to (weakly) cause the former with a p-value of 0.0867, corresponding to a $\chi^2(1)$ test statistic of 2.9350. The FSIs are available at: https://policyuncertainty.com/FSI.html.

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Table 1. Clark and West (2007) forecast comparison test *p*-values for daily data: 15th January 2010-28th February 2025

		h				
	Models	1	5	22	44	66
China	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M2	0.0000	0.2035	0.0000	0.0001	0.0000
	M4 vs M2	0.0000	0.0000	0.0000	0.0003	0.0014
	M4 vs M3	0.0000	0.0000	0.0000	0.0787	0.1638
		h				
	Models	1	5	22	44	66
France	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M2	0.0013	0.0025	0.5100	0.4234	0.4845
	M4 vs M2	0.0000	0.0085	0.0226	0.0778	0.1152
	M4 vs M3	0.0000	0.0579	0.0154	0.0667	0.0932
		h				
	Models	1	5	22	44	66
Germany	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M2	0.0107	0.6104	0.5794	0.9094	0.8201
	M4 vs M2	0.0002	0.1274	0.0869	0.1192	0.2378
	M4 vs M3	0.0000	0.0396	0.0093	0.0007	0.0196
		h				
	Models	1	5	22	44	66
Italy	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M2	0.8247	0.8731	0.6810	0.6726	0.8955
	M4 vs M2	0.0000	0.0214	0.0815	0.0616	0.0963
	M4 vs M3	0.0001	0.0136	0.0720	0.0546	0.0620
		h				
	Models	1	5	22	44	66
Spain	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M2	0.0001	0.0011	0.0140	0.0386	0.1085
	M4 vs M2	0.0000	0.0902	0.1212	0.2201	0.0332
	M4 vs M3	0.0000	0.2620	0.3198	0.4320	0.0750
		h				
	Models	1	5	22	44	66
UK	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000

	M3 vs M2	0.0003	0.0485	0.6059	0.3453	0.5693
	M4 vs M2	0.0000	0.0006	0.0400	0.1693	0.0328
	M4 vs M3	0.0000	0.0065	0.0348	0.2181	0.0351
		h				
	Models	1	5	22	44	66
US	M2 vs M1	0.0000	0.0000	0.0000	0.0104	0.1337
	M3 vs M1	0.0000	0.0000	0.0000	0.0139	0.1611
	M4 vs M1	0.0000	0.0000	0.0000	0.0118	0.0898
	M3 vs M2	0.0047	0.8392	0.5101	0.6649	0.7770
	M4 vs M2	0.0000	0.0501	0.0458	0.1057	0.0265
	M4 vs M3	0.0000	0.0047	0.0267	0.0571	0.0060

Note: The entries in all rows are *p*-values of the Clark and West (2007) test of forecast comparison across two nested models, with the null being forecast equality, and the alternative is that the rival model outperforms the benchmark. *h* is the forecast horizon. M1 is the benchmark model of the inter-quantile range (IQR) of stock returns of a particular country which includes a constant and 3 lags each of own- and cross-country IQRs; M2 is M1+own- and cross-country moments (leverage, skewness, kurtosis, lower- and upper-tail risks); M3 is M2+own-country Supply Bottlenecks Index (SBI); M4 is M3+ SBI of the other countries.

APPENDIX

Table A1. Root Mean Square Errors (RMSEs) for daily data: 15th January 2010-28th February 2025

		h				
	Models	1	5	22	44	66
China	M1	0.0037	0.0072	0.0114	0.0133	0.0150
	M2 vs M1	0.7727	0.9605	1.0040	0.9888	0.9933
	M3 vs M1	0.7598	0.9652	0.9993	0.9846	0.9894
	M4 vs M1	0.7575	0.9600	0.9947	0.9862	0.9909
	M3 vs M2	0.9834	1.0048	0.9953	0.9958	0.9961
	M4 vs M2	0.9804	0.9995	0.9907	0.9974	0.9976
	M4 vs M3	0.9970	0.9946	0.9954	1.0016	1.0015
		h				
	Models	1	5	22	44	66
France	M1	0.0031	0.0061	0.0122	0.0147	0.0158
	M2 vs M1	0.5713	0.9212	0.9847	0.9921	0.9947
	M3 vs M1	0.5690	0.9171	0.9851	0.9922	0.9950
	M4 vs M1	0.5593	0.9196	0.9825	0.9910	0.9940
	M3 vs M2	0.9959	0.9955	1.0004	1.0001	1.0002
	M4 vs M2	0.9789	0.9983	0.9978	0.9990	0.9992
	M4 vs M3	0.9830	1.0028	0.9974	0.9988	0.9990
		h				
	Models	1	5	22	44	66
Germany	M1	0.0028	0.0056	0.0114	0.0139	0.0150
	M2 vs M1	0.4746	0.9005	0.9808	0.9941	0.9948
	M3 vs M1	0.4721	0.9040	0.9817	0.9964	0.9963
	M4 vs M1	0.4676	0.9020	0.9796	0.9933	0.9946
	M3 vs M2	0.9949	1.0038	1.0009	1.0023	1.0015
	M4 vs M2	0.9852	1.0016	0.9987	0.9992	0.9998
	M4 vs M3	0.9903	0.9978	0.9978	0.9969	0.9983
		h				
	Models	1	5	22	44	66
Italy	M1	0.0043	0.0084	0.0156	0.0179	0.0188
	M2 vs M1	0.5682	0.9183	0.9864	0.9953	0.9937
	M3 vs M1	0.5800	0.9214	0.9871	0.9958	0.9948
	M4 vs M1	0.5513	0.9134	0.9844	0.9928	0.9920
	M3 vs M2	1.0208	1.0034	1.0007	1.0006	1.0011
	M4 vs M2	0.9703	0.9947	0.9980	0.9975	0.9982
	M4 vs M3	0.9506	0.9913	0.9972	0.9969	0.9972
		h				
	Models	1	5	22	44	66
Spain	M1	0.0030	0.0060	0.0119	0.0140	0.0147
	M2 vs M1	0.7081	0.9355	0.9795	0.9891	0.9903
	M3 vs M1	0.7087	0.9331	0.9779	0.9880	0.9897
	M4 vs M1	0.7170	0.9460	0.9807	0.9905	0.9893
	M3 vs M2	1.0009	0.9974	0.9984	0.9989	0.9994

	M4 vs M2	1.0125	1.0112	1.0012	1.0014	0.9990
	M4 vs M3	1.0116	1.0139	1.0028	1.0025	0.9996
		h				
	Models	1	5	22	44	66
UK	M1	0.0026	0.0051	0.0101	0.0121	0.0128
	M2 vs M1	0.6462	0.9398	0.9839	0.9873	0.9902
	M3 vs M1	0.6428	0.9389	0.9853	0.9875	0.9910
	M4 vs M1	0.6111	0.9369	0.9824	0.9875	0.9877
	M3 vs M2	0.9947	0.9990	1.0014	1.0001	1.0008
	M4 vs M2	0.9456	0.9969	0.9984	1.0002	0.9975
	M4 vs M3	0.9506	0.9979	0.9970	1.0001	0.9967
		h				
	Models	1	5	22	44	66
US	M1	0.0034	0.0067	0.0142	0.0171	0.0181
	M2 vs M1	0.5742	0.9357	0.9933	1.0029	1.0081
	M3 vs M1	0.5749	0.9390	0.9936	1.0034	1.0087
	M4 vs M1	0.5642	0.9373	0.9922	1.0024	1.0068
	M3 vs M2	1.0013	1.0034	1.0003	1.0005	1.0006
	M4 vs M2	0.9825	1.0016	0.9989	0.9996	0.9987
	M4 vs M3	0.9813	0.9982	0.9986	0.9991	0.9981

Note: The entries in the row named M1 is the absolute RMSEs of M1, while for the other rows the entries are relative RMSEs of the first named model (*i*) relative to (vs) the second (*j*), with a value less than 1 suggesting the former outperforms the latter. *h* is the forecast horizon. M1 is the benchmark model of the inter-quantile range (IQR) of stock returns of a particular country which includes a constant and 3 lags each of own- and cross-country IQRs; M2 is M1+own- and cross-country moments (leverage, skewness, kurtosis, lower- and upper-tail risks); M3 is M2+own-country Supply Bottlenecks Index (SBI); M4 is M3+ SBI of the other countries.

Table A2. Clark and West (2007) forecast comparison test *p*-values for monthly data: January 1900- December 2024

		h				
	Models	1	3	6	12	24
Canada	M2 vs M1	0.4121	0.4110	0.3298	0.1700	0.2228
	M3 vs M1	0.2017	0.2040	0.1351	0.0433	0.0656
	M4 vs M1	0.4925	0.4887	0.3895	0.2295	0.2740
	M3 vs M2	0.0653	0.0668	0.0678	0.0785	0.0620
	M4 vs M2	0.7737	0.7684	0.7009	0.6591	0.6522
	M4 vs M3	0.8719	0.8689	0.8405	0.8119	0.8287
		h				
	Models	1	3	6	12	24
France	M2 vs M1	0.0402	0.0378	0.0402	0.0405	0.0202
	M3 vs M1	0.0374	0.0356	0.0344	0.0333	0.0131
	M4 vs M1	0.0298	0.0325	0.0376	0.0320	0.0149
	M3 vs M2	0.0989	0.1203	0.0551	0.0439	0.0318
	M4 vs M2	0.1277	0.1515	0.1637	0.1368	0.1387
	M4 vs M3	0.1388	0.1644	0.2063	0.1750	0.1859
		h				
	Models	1	3	6	12	24
Germany	M2 vs M1	0.6895	0.6798	0.6726	0.6651	0.6684
	M3 vs M1	0.7470	0.7417	0.7365	0.7295	0.7327
	M4 vs M1	0.6746	0.6670	0.6595	0.6488	0.6539
	M3 vs M2	0.8559	0.8596	0.8558	0.8506	0.8485
	M4 vs M2	0.1815	0.1916	0.1972	0.1984	0.1989
	M4 vs M3	0.1437	0.1438	0.1438	0.1434	0.1438
		h				
	Models	1	3	6	12	24
Japan	M2 vs M1	0.0004	0.0011	0.0000	0.0001	0.0046
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0001
	M4 vs M1	0.0002	0.0003	0.0004	0.0009	0.0013
	M3 vs M2	0.1160	0.1126	0.0856	0.1056	0.0996
	M4 vs M2	0.0863	0.0984	0.0830	0.0934	0.0670
	M4 vs M3	0.0708	0.0965	0.0969	0.0950	0.0505
		h				
	Models	1	3	6	12	24
UK	M2 vs M1	0.0172	0.0222	0.0425	0.0312	0.0581
	M3 vs M1	0.0253	0.0405	0.0909	0.0780	0.1597
	M4 vs M1	0.0570	0.0883	0.1639	0.1261	0.2607
	M3 vs M2	0.8073	0.9092	0.9655	0.9885	0.9943
	M4 vs M2	0.7322	0.7759	0.8163	0.8620	0.9010
	M4 vs M3	0.6184	0.5970	0.5742	0.5601	0.6042
		h				
	Models	1	3	6	12	24
US	M2 vs M1	0.0080	0.0118	0.0057	0.0035	0.0044
	M3 vs M1	0.0257	0.0308	0.0209	0.0159	0.0161
	M4 vs M1	0.0129	0.0179	0.0093	0.0070	0.0076

	M3 vs M2	0.0810	0.0764	0.0718	0.0910	0.0764
	M4 vs M2	0.0493	0.0671	0.0370	0.1046	0.0501
	M4 vs M3	0.7498	0.8470	0.5957	0.7506	0.7998

Note: The entries in all rows are *p*-values of the Clark and West (2007) test of forecast comparison across two nested models, with the null being forecast equality, and the alternative is that the rival model outperforms the benchmark. *h* is the forecast horizon. M1 is the benchmark model of the inter-quantile range (IQR) of stock returns of a particular country which includes a constant and 2 lags each of own- and cross-country IQRs; M2 is M1+own- and cross-country moments (leverage, skewness, kurtosis, lower- and upper-tail risks); M3 is M2+own-country Shortages Index; M4 is M3+ Shortages Index of the other countries.

Table A3. Clark and West (2007) forecast comparison test p-values for daily data: 15th January 2010-28th February 2025

		h				
	Models	1	5	22	44	66
China	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0001
	M3 vs M2	0.0000	0.0049	0.0075	0.0127	0.1492
	M4 vs M2	0.0000	0.0007	0.0749	0.1784	0.4182
	M4 vs M3	0.0000	0.0069	0.3819	0.6875	0.6148
		h				
	Models	1	5	22	44	66
Europe	M2 vs M1	0.0000	0.0000	0.0000	0.0002	0.0000
	M3 vs M1	0.0000	0.0000	0.0000	0.0073	0.0010
	M4 vs M1	0.0000	0.0000	0.0000	0.0001	0.0000
	M3 vs M2	0.0027	0.1302	0.6006	0.8659	0.8875
	M4 vs M2	0.0001	0.0032	0.0208	0.0123	0.0067
	M4 vs M3	0.0001	0.0009	0.0018	0.0000	0.0000
		h				
	Models	1	5	22	44	66
UK	M2 vs M1	0.0000	0.0000	0.0000	0.0002	0.0000
	M3 vs M1	0.0000	0.0000	0.0001	0.0017	0.0004
	M4 vs M1	0.0000	0.0000	0.0000	0.0004	0.0000
	M3 vs M2	0.0300	0.0428	0.1099	0.1334	0.1113
	M4 vs M2	0.0000	0.0001	0.0214	0.0296	0.0063
	M4 vs M3	0.0000	0.0006	0.1319	0.1388	0.0385
		h				
	Models	1	5	22	44	66
US	M2 vs M1	0.0000	0.0000	0.0000	0.0014	0.0106
	M3 vs M1	0.0000	0.0000	0.0000	0.0017	0.0185
	M4 vs M1	0.0000	0.0000	0.0000	0.0011	0.0065
	M3 vs M2	0.2534	0.9268	0.9365	0.9256	0.9598
	M4 vs M2	0.0000	0.0875	0.1655	0.0987	0.0826
	M4 vs M3	0.0013	0.0354	0.0403	0.0236	0.0125

Note: The entries in all rows are p-values of the Clark and West (2007) test of forecast comparison across two nested models, with the null being forecast equality, and the alternative is that the rival model outperforms the benchmark. h is the forecast horizon. M1 is the benchmark model of the inter-quantile range (IQR) of stock returns of a particular country which includes a constant and 10 lags each of own- and cross-country IQRs; M2 is M1+own- and cross-country moments (leverage, skewness, kurtosis, lower- and upper-tail risks); M3 is M2+own-country Supply Bottlenecks Index (SBI); M4 is M3+ SBI of the other countries.