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Supply bottlenecks and machine learning forecasting of international stock market volatility

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A B S T R A C T

This study explores the information value of the daily Supply Bottlenecks Index (SBI) – derived from newspaper articles – to forecast daily return volatilities of seven major developed stock markets: China, France, Germany, Italy, Spain, the UK, and the US. Volatility is measured using the interquantile range, obtained through an asymmetric slope autoregressive quantile regression model applied to stock returns to estimate conditional quantiles. From this, we derive key distributional moments including skewness, kurtosis, and lower- and upper-tail risks, which are then incorporated into a linear forecasting framework alongside leverage effects. Using Lasso shrinkage techniques to address potential overfitting, we find that the model incorporating higher-order moments outperforms a benchmark model based solely on own- and cross-country volatilities. Notably, the predictive accuracy improves further when supply constraint indicators from all seven countries are included. These results hold important implications for investors as we later highlighted.

1. Introduction

In recent years, the global economy has experienced multiple severe supply-side shocks, with the COVID-19 pandemic standing out as a particularly disruptive event, following a period of relative calm since the global financial crisis (GFC). A wide range of research has demonstrated that the consequences of such supply disruptions (i.e., supply bottlenecks) transcend traditional macroeconomic outcomes including elevated inflation, reduced output, and weaker labour markets (Diaz et al., 2023; Asadollah et al., 2024; Ascari et al., 2024; Tillmann, 2024; Ginn and Saadaoui, 2025a). These disruptions also affect financial markets, leading to falling equity prices and reduced leverage (see, for instance, Hupka, 2022; Smirnyagin and Tsyvinski, 2022; Burriel et al., 2024; Ginn, 2024; Ginn

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and Saadaoui, 2025b).[1]

Building on previous insights and aiming to further highlight the significance of supply chain disruptions on financial markets, this study investigates the predictive potential of the recently developed daily Supply Bottlenecks Index (SBI) by Burriel et al. (2024). Constructed from newspaper article contents, the index is used in forecasting stock market volatilities of China, France, Germany, Italy, Spain, the United Kingdom, and the United States spanning January 2010 through February 2025. Thus, this work adds to the growing body of research focused on the financial implications of supply-side constraints.

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., key distributional moments such as leverage, skewness, kurtosis, and lower- and upper-tail risks, as highlighted by Foglia et al. (2025a, 2025b). Note that, recent studies (see, for reference, 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.

For the empirical exercise, we firstly apply the asymmetric slope autoregressive quantile regression model of Engle and Manganelli (2004) on the stock returns data. This method enables us to estimate volatility as the interquantile range derived from conditional quantiles within a univariate setup. We must also point out that the interquantile range is considered to be a robust measure of uncertainty (volatility) risk based on conditional quantiles (Ghysels et al., 2018). This is because the interquantile range pertains to the information about the possible future range of the realized stock returns. All else being equal, as the interquantile range increases, extreme stock returns realizations are more likely to occur, which, in turn, is particularly appropriate in our context, as we are trying to analyze the role of SBIs, characterized by sudden spikes. Furthermore, a key benefit of this asymmetric slope autoregressive quantile regression approach is that it also allows us to extract additional distributional characteristics of stock returns, namely: skewness, kurtosis, and both lower- and upper-tail risks. These metrics, together with leverage (captured through negative returns) serve as our control variables in our model. Subsequently, we implement a linear regression framework for forecasting volatility, using the least absolute shrinkage and selection operator (Lasso) technique developed by Tibshirani (1996). This choice is motivated by the large number of potential predictors, ranging from 22 to 64, arising from the inclusion of own- and cross-country lags of volatility, higher-order moments, and supply bottleneck indices (SBIs), all assessed over rolling 250-day (one-year) windows.

At this point, it is imperative to discuss some theoretical underpinnings that can be used to hypothesize the causal relationship from supply bottlenecks to stock market volatility of our analysis by realizing that the SBI encompassing not just strikes and price regulations, but also broader disruptions such as geopolitical tensions, climate-related catastrophes, pandemics, and trade wars, often serve as a "catch-all" empirical proxy for infrequent but severe economic shocks (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 both Wachter (2013) as well as Tsai and Wachter (2015). These two papers construct theoretical frameworks where overall consumption typically exhibits a stable pattern with low variability and follows a 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. In other words, these models account for the risks linked to rare disaster events. The likelihood of such extreme outcomes significantly decreases stock returns and increases the equity premium. Additionally, it contributes to high stock market volatility because of the fluctuating probability of these disasters occurring. Besides, with SBIs known to negatively influence macroeconomic variables in the form of higher inflation and lower output, both of which are recognized as key drivers of asset prices (Schwert, 1989), would convey "bad news" for financial markets. Consequently, this is likely to increase the risk profile of equities and hence, raise its volatility (Engle et al., 2013).[2]

Since stock return volatility has an important role in portfolio construction, hedging strategies, and the pricing of derivative instruments, producing accurate volatility forecasts is essential for effective risk and asset management (Rapach et al., 2008). As such, this empirical exercise is of pertinent important and holds practical relevance for investors, beyond its academic value. To our knowledge, this is the first study to assess the predictive performance of Supply Bottlenecks Indexes (SBIs) for international stock return volatility using a linear machine learning approach. In the process, our work focuses on out-of-sample predictability and extends Bouri et al. (2025), who provide evidence of in-sample predictability of the conditional distribution (returns and volatility) for these seven financial markets utilizing a bivariate causality-in-quantiles approach. However, as it is quite well-discussed (see, for example, Rapach and Zhou, 2022; Goyal et al., 2024), in-sample predictability of stock price movements does not guarantee improved out-of-sample forecast accuracy, which is a more rigorous standard for evaluating model performance. Against this backdrop, this

[1] In this regard, these papers can be considered to be building on the works of Hendricks and Singhal (2003, 2005a, 2005b) 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.

[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., 2023b). 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/.

study add to enormous body of knowledge that develops and evaluates both linear and nonlinear models across univariate and multivariate frameworks to forecast volatility in international equity markets (refer to Poon and Granger (2003), Corsi et al. (2012), Bhowmik and Wang (2020), Dhingra et al. (2024) for review).

To actualize the study's main objective, other sections complementing this introduction are organized in the following manner. Section 2 offers the description of the utilised data, while Section 3 gives the outline of the adopted technique upon which the empirical results are anchored. In this section, we also presents and discusses our results. Finally, we conclude in Section 4.

2. Some data considerations

As our main explanatory variable, we employ the daily Supply Bottlenecks Index (SBI) developed by Burriel et al. (2024) for seven major economies: China, France, Germany, Italy, Spain, the UK, and the US.[3] This index is constructed by tracking the relative frequency of newspaper articles that simultaneously contain terms related to supply chains (including "supply chain, supply chains, supply, supplies") and language indicating negative sentiment or disruptions (including "bottleneck, bottlenecks, shortage, shortages, woe, woes, disruption, disruptions, problem, problems, scarcity, scarcities, lack, delay, delays, backlog, backlogs"). An article is classified as highlighting supply chain issues only if it contains at least one word from each group within a 10-word span.[4] Consequently, SBI indexes offer a unique and timely (real-time) way of capturing supply chain disturbances based on media sources.

For stock market data, we use the respective country's stocks indices, namely: SHCOMP, CAC 40, DAX, FTSEMIB, IBEX 35, FTSE 100, and S&P 500, all sourced from Bloomberg. Consequent upon calculating the two-day log-returns of these indices, we apply the asymmetric slope autoregressive quantile regression model 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 model captures persistent, asymmetric effects of past or lagged observations on the respective quantiles, dictated by whether returns exceed or lack the unconditional mean. As a result, the model accommodates differing effects of positive and negative market movements (including bearish/bullish) on the distribution of returns, and thereby allow for downside and upside risks to evolve independently. Next, we fit and get the conditional quantiles for the country-wise two-day log returns on stocks $(\widehat{Q_t^p})$ for $p = 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95$, and 0.99, along with a leverage indicator (LEV), which marks days with negative raw stock log-returns, we extract several distributional features: lower-tail risk (LTR), upper-tail risk (UTR), skewness (SKEW), and kurtosis (KURT). These are then used as inputs to forecast our volatility measure, namely the inter-quantile range (IQR), for stock returns. In line with Gupta et al. (2023a), 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 $= (\widehat{Q_t^{0.99}} - \widehat{Q_t^{0.01}})/(\widehat{Q_t^{0.75}} - \widehat{Q_t^{0.25}})$.[5]

It must be pointed out that the decision to compute two-day log-returns emanate from the fact that the markets have different opening and closing times, and allow us to prevent the possibility of any look-ahead-bias (Ehrmann et al., 2011; Lombardi et al., 2019).[6] Given the common starting point of the SBI indexes, our analysis is for the time period between January 15th, 2010 and February 28th, 2025, with the untransformed SBIs used as predictors, over and above the stock market moment.

3. Empirical modelling and discussion of results

Following the above, we specify our predictive model as follows: For forecasting horizon h (months)

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

where IQR_{t+h}, stands for the average volatility for the period from t and $t+h$, with volatility being measured using the interquantile range (IQR) derived from quantiles estimated via the asymmetric slope autoregressive quantile regression. Meanwhile, Z_t denotes the vector of predicting variables, which differ depending on the specific model being analyzed, as detailed below and γ is the corresponding unknown coefficient-vector. The term ϵ_{t+h} captures the usual error component, c stands for the intercept term representing the conditional expectation of IQR_{t+h}.

In the baseline model (i.e., M1), the predictor set X_t consists of seven lags of the IQR_t for each of the seven stock markets.[7] These lag

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

[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.

[5] Ideally, one should have used intraday data to compute the various daily moments, however, we do not have access to intraday data. Moreover, because we also provide an analysis involving historical monthly data starting in 1900, over which no intraday data is available, we resorted to the asymmetric slope autoregressive quantile regression model to determine our moments for the sake of comparability of the approach undertaken for the computation of the underlying moments.

[6] We would like to thank the anonymous referee for pointing this out to us, as the previous version of this paper had relied on one-day log-returns.

[7] Based on the suggestions of an anonymous referee, when we compared the full-sample fit of the benchmark model of IQR with 250-days rolling variance, univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), and Heterogeneous Autoregressive Realized Volatility with Jumps (HAR-RV-J) models, with RV data derived from the Oxford-Man Institute of Quantitative Finance, over the common sample period of 15th January 2010 to 2nd June 2021, the IQR model with lags of itself and the six other countries produced the lowest Mean Square Errors (MSEs), except for Germany. Complete details of these results are available upon request from the authors.

length is selected using the Akaike Information Criterion (AIC) so as to account for volatility interconnectedness. Model 2 (i.e., M2) expands upon M1 by incorporating leverage (LEV), skewness (SKEW), kurtosis (KURT), and both lower- and upper-tail risks (LTR and UTR), of not only the particular stock market volatility that we are forecasting, but also for the other six. Model 3 (M3) further augments this by adding own-country SBI to the predictors. Finally, Model 4 (M4) expands the covariate set of M3 by incorporating other country's SBIs.

Given this framework, the models M1 through M4 include 22, 57, 58, and 64 predictors respectively. To manage the high dimensionality within a rolling-window forecasting approach, using 250 daily observations at each step, we apply the widely used Lasso shrinkage technique. This method helps address the risk of overfitting and potential deterioration in out-of-sample forecast accuracy. The core principle behind Lasso is that apart from estimating the important coeffcients, it also simultaneously performs a variable selection and thus reduces it to a parsimonious model with better interpretability and enhance predictive performance. Mathematically speaking, this is achieved through proper penalization as follows:

$$\hat{\gamma}_{Lasso} = \operatorname{argmin}\left(\sum_{t=1}^{T}\left(IQR_{t+h} - c - Z_t\gamma\right)^2 + \lambda\sum_{j=1}^{n}\left|\gamma_j\right|\right) \tag{2}$$

From the above Eq. (2), we set T to be the size of 'training window' that is used to construct the model for forecasting, λ being the shrinkage parameter. The Lasso approach modifies the standard ordinary least squares (OLS) method by introducing a penalty term proportional to the sum of the absolute values of the coefficients. This penalty discourages large coefficient estimates, effectively shrinking some of them toward zero. The trade-off between minimizing the prediction error and applying this penalty determines which coefficients remain in the model, and a non-zero estimate suggests those predictors are relevant.[8]

In our forecasting framework, we treat the first year (250 trading days) as the in-sample period and apply a rolling-window strategy, advancing the window by one observation at a time until the period 28/02/2025 to generate forecasts for horizons $h = 1$, 5, 22, 44, and 66 days ahead. This allowed us to cover a long out-of-sample period involving prolonged episodes of low and high SBIs.[9] To eliminate the possibility of look-ahead bias when computing skewness, kurtosis, and both lower- and upper-tail risks, we re-estimate the asymmetric slope autoregressive quantile regression across the relevant quantiles, while also maintaining a 250-day ahead rolling window.

To make our disposition complete, in the Appendix, the Root Mean Square Errors (RMSEs) of model M1, as well as those of models M2, M3, and M4 relative to M1; M3 and M4 relative to M2, and; M4 relative to M3 (see Table A1) are presented. However, to get a clear inference from our forecasting results, given the similar-sized RMSEs of M2, M3 and M4, we focus primarily on the Clark and West (2007) test to draw more meaningful conclusions from the forecasting performance 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). Thus, the CW test examines whether the larger, more complex model provides significantly better forecasts than the simpler, nested one. Both models have equal predictive ability under the null hypothesis, while the alternative hypothesis favours the larger model. The CW test, being one-sided, produces p-values reported in Table 1 for M2, M3 and M4 versus M1; M3 and M4 versus M2, and; M4 versus M3.

As revealed in Table 1, models 1, 3 and 4, consistently surpasses the benchmark M1 containing lagged volatilities of all the 7 equity markets in a statistically significant manner (primarily at the 1 % level) for each of the five forecast horizons $h = 1$, 5, 22, 44, and 66. 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 resulting from the CW test statistics, indicate that out of the maximum possible 35 cases, in 15 instances (43 % of times),[10] particularly at medium- to long-run, M3 fails to outperform M2. In other words, taken together, economy-specific SBIs tend to perform better than

[8] For our forecasting exercise, we use the Glmnet package in R, which fits generalized linear and similar models via penalized maximum likelihood. In this regard, when choosing the regularization parameter λ, updated in each iteration over the out-of-sample period, we have used the option: lambda.1se, which represents the largest value of λ such that the cross-validated error is within one standard error of the minimum cross-validated error.

[9] Based on the suggestions of an anonymous referee, we also experimented with 500- and 1000-days rolling window. Our results, available upon request from the authors, were qualitatively similar.

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

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	0.0000	0.0163	0.1678	0.2027
	M4 vs M2	0.0000	0.0000	0.0091	0.1153	0.1951
	M4 vs M3	0.2990	0.5707	0.5503	0.2836	0.5939
		h				
	Models	1	5	22	44	66
France	M2 vs M1	0.0000	0.0000	0.0000	0.0000	0.0022
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0031
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0012
	M3 vs M2	0.2496	0.8664	0.8901	0.9216	0.9927
	M4 vs M2	0.0000	0.0000	0.0054	0.1927	0.1929
	M4 vs M3	0.0000	0.0000	0.0027	0.1319	0.0954
		h				
	Models	1	5	22	44	66
Germany	M2 vs M1	0.0000	0.0000	0.0587	0.0273	0.0096
	M3 vs M1	0.0000	0.0000	0.0584	0.0294	0.0124
	M4 vs M1	0.0000	0.0000	0.0148	0.0077	0.0023
	M3 vs M2	0.3468	0.2310	0.3626	0.5212	0.7591
	M4 vs M2	0.0007	0.0000	0.0043	0.0167	0.0167
	M4 vs M3	0.0009	0.0000	0.0059	0.0170	0.0144
		h				
	Models	1	5	22	44	66
Italy	M2 vs M1	0.0000	0.0000	0.0001	0.0052	0.0737
	M3 vs M1	0.0000	0.0000	0.0000	0.0001	0.0002
	M4 vs M1	0.0000	0.0000	0.0000	0.0001	0.0007
	M3 vs M2	0.0000	0.0000	0.0004	0.0011	0.0002
	M4 vs M2	0.0000	0.0000	0.0008	0.0022	0.0009
	M4 vs M3	0.2573	0.8548	0.9153	0.9373	0.9922
		h				
	Models	1	5	22	44	66
Spain	M2 vs M1	0.0000	0.0000	0.0000	0.0367	0.0289
	M3 vs M1	0.0000	0.0000	0.0000	0.0109	0.0085
	M4 vs M1	0.0000	0.0000	0.0000	0.0131	0.0102
	M3 vs M2	0.0000	0.0000	0.0050	0.0845	0.0600
	M4 vs M2	0.0000	0.0000	0.0098	0.1121	0.0783
	M4 vs M3	0.6388	0.9592	0.9473	0.8200	0.7799
		h				
	Models	1	5	22	44	66
UK	M2 vs M1	0.0000	0.0000	0.0047	0.0068	0.0020
	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	0.0000	0.0000	0.0000	0.0002
	M4 vs M2	0.0000	0.0000	0.0000	0.0000	0.0001
	M4 vs M3	0.0010	0.5256	0.1320	0.3125	0.3544
		h				
	Models	1	5	22	44	66
US	M2 vs M1	0.0000	0.0000	0.0007	0.0669	0.0853
	M3 vs M1	0.0000	0.0000	0.0001	0.0114	0.0185
	M4 vs M1	0.0000	0.0000	0.0002	0.0157	0.0213
	M3 vs M2	0.0000	0.0000	0.1217	0.1105	0.1221
	M4 vs M2	0.0000	0.0000	0.1772	0.1508	0.1430
	M4 vs M3	0.1668	0.8798	0.8060	0.7161	0.6097

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 7 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.

own- and cross-country moments in forecasting stock market IQR. Furthermore, when we also consider the role of other country SBIs in the model, i.e., M4, the performance improves further, with this model outperforming M2 in 27 out of the 35 cases,[11] i.e., in 77 % of the instances (compared to 57 % of cases). 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.[12] Although, it must be noted that, in 25 out of 35 cases (i.e., 71 % of times), M3 and M4 perform equally well in the statistical sense.[13]

Besides the Clark and West (2007) pairwise model tests, in Table 2, we also report the results from multi-model comparisons using the Model Confidence Set (MCS) test of Hansen et al. (2001). Based on the MCS test, using the MSE loss function (to be consistent with the Clark and West (2007) test), M4 emerges as the top-performing model overall, with M3 also serving as a very strong competitor. The results clearly indicate a two-way contest between M3 and M4, thus demonstrating the substantial gains emanating from own- and cross-country SBIs in forecasting stock returns volatility of the 7 countries considered, even beyond a pairwise context.[14]

In sum, the information content of supply bottlenecks in forecasting the future trajectory 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, especially when, we include cross-country SBIs in addition to its own values of the same in the forecasting set-up.[15] 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.

4. Conclusion

We forecast the daily stock return volatilities of China, France, Germany, Italy, Spain, the UK, and the US from January 2010 to February 2025, drawing from information embedded in newspaper-based indexes that capture supply bottlenecks. Volatility is quantified using the interquantile range, which we estimate via an asymmetric slope autoregressive quantile regression applied to stock return data. This method also facilitates the extraction of higher-order distributional features such as skewness, kurtosis, and tail risks, which are integrated into a linear forecasting framework alongside leverage effects. To mitigate overparameterization, we employ a Lasso shrinkage approach. The model incorporating these distributional moments demonstrates superior forecasting performance compared to a baseline model that includes both own- and cross-country volatilities. Furthermore, predictive accuracy improves when the metrics of supply constraints for all the 7 countries are simultaneously considered.

Given that it is important to accurately forecast volatility for optimal portfolio construction, our results highlight that including information content of both own (i.e., domestic) and, in particular, cross-country supply bottlenecks, over and above realized moments, in predictive models of volatility of the seven stock market can enhance investors' asset allocation strategies across varying time horizons.

As part of further research, one could build on our analysis to have 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, 2019b), future work can be pursued in relating supply constraints with overall financial stress

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

[12] 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 CW test 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.

[13] The ten cases where M4 outperforms M3 are: for France at $h = 1$, 5, 22 and 66; for Germany at $h = 1$, 5, 22, 44, and 66, and; for the UK at $h = 1$.

[14] Similar observations, barring the case of Germany, was drawn when we used the Quasi-Likelihood (QLIKE) loss metric, instead of the MSE, in the MCS test, as suggested by an anonymous referee. These results are available upon request from the authors.

[15] Based on the results of the CW test as given 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, but 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.

Table 2
Model Confidence Set (MCS) test results for daily data: 15th January 2010–28th February 2025.

Country, Horizon	M1	M2	M3	M4
China, $h = 1$	elim.	elim.	1	2
China, $h = 5$	elim.	elim.	2	1
China, $h = 22$	3	4	2	1
China, $h = 44$	3	elim.	2	1
China, $h = 66$	1	elim.	3	2
France, $h = 1$	elim.	elim.	elim.	1
France, $h = 5$	elim.	elim.	elim.	1
France, $h = 22$	2	4	3	1
France, $h = 44$	1	elim.	elim.	elim.
France, $h = 66$	1	elim.	elim.	elim.
Germany, $h = 1$	2	3	4	1
Germany, $h = 5$	elim.	elim.	elim.	1
Germany, $h = 22$	1	3	4	2
Germany, $h = 44$	1	3	4	2
Germany, $h = 66$	1	elim.	elim.	2
Italy, $h = 1$	elim.	elim.	1	2
Italy, $h = 5$	elim.	elim.	elim.	1
Italy, $h = 22$	elim.	elim.	2	1
Italy, $h = 44$	elim.	elim.	elim.	1
Italy, $h = 66$	elim.	elim.	2	1
Spain, $h = 1$	elim.	elim.	1	2
Spain, $h = 5$	elim.	elim.	1	2
Spain, $h = 22$	3	4	1	2
Spain, $h = 44$	3	4	1	2
Spain, $h = 66$	3	4	1	2
UK, $h = 1$	elim.	elim.	2	1
UK, $h = 5$	elim.	elim.	1	elim.
UK, $h = 22$	3	elim.	1	2
UK, $h = 44$	3	elim.	2	1
UK, $h = 66$	3	elim.	1	2
US, $h = 1$	elim.	elim.	2	1
US, $h = 5$	elim.	elim.	1	elim.
US, $h = 22$	1	4	3	2
US, $h = 44$	1	4	3	2
US, $h = 66$	1	4	3	2

Note: See Notes to Table 1. The table displays the performance rank for each model, i.e., M1, M2, M3 and M4, based on the Model Confidence Set (MCS) test of Hansen et al. (2001). A lower number signifies better performance. Models that were statistically outperformed and removed from the set of superior models are marked as "elim.".

of a set of developed and developing countries.[16]

CRediT authorship contribution statement

Dhanashree Somani: Software, Methodology, Investigation, Formal analysis. **Rangan Gupta:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Data curation, Conceptualization. **Sayar Karmakar:** Writing – review & editing, Supervision, Software, Methodology, Investigation, Formal analysis. **Vasilios Plakandaras:** Writing – review & editing, Supervision, Project administration, Investigation.

Declaration of competing interest

All the authors declare no conflict of interest.

Appendix

Tables A1, A2, A3

[16] 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.

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	0.0132	0.0283	0.0600	0.0802	0.0883
	M2 vs M1	0.3192	0.9009	0.9909	0.9972	0.9963
	M3 vs M1	0.2733	0.8809	0.9883	0.9963	0.9955
	M4 vs M1	0.2742	0.8811	0.9883	0.9961	0.9956
	M3 vs M2	0.8559	0.9778	0.9973	0.9991	0.9992
	M4 vs M2	0.8590	0.9781	0.9974	0.9989	0.9993
	M4 vs M3	1.0036	1.0003	1.0001	0.9998	1.0001
		h				
	Models	1	5	22	44	66
France	M1	0.0523	0.1300	0.2854	0.3454	0.3751
	M2 vs M1	0.4268	0.9275	0.9900	0.9951	1.0002
	M3 vs M1	0.4285	0.9281	0.9902	0.9953	1.0005
	M4 vs M1	0.4026	0.9112	0.9875	0.9947	0.9997
	M3 vs M2	1.0039	1.0006	1.0002	1.0002	1.0004
	M4 vs M2	0.9433	0.9825	0.9975	0.9995	0.9995
	M4 vs M3	0.9396	0.9818	0.9973	0.9993	0.9992
		h				
	Models	1	5	22	44	66
Germany	M1	0.1351	0.3651	0.6665	0.7541	0.7770
	M2 vs M1	1.1899	1.0196	1.0207	1.0182	1.0148
	M3 vs M1	1.1892	1.0191	1.0206	1.0183	1.0152
	M4 vs M1	0.9472	0.9386	1.0136	1.0122	1.0092
	M3 vs M2	0.9994	0.9995	0.9999	1.0001	1.0004
	M4 vs M2	0.7960	0.9206	0.9930	0.9941	0.9944
	M4 vs M3	0.7965	0.9211	0.9931	0.9941	0.9940
		h				
	Models	1	5	22	44	66
Italy	M1	0.0276	0.0913	0.1761	0.2022	0.2225
	M2 vs M1	0.8615	0.9579	0.9968	0.9989	1.0008
	M3 vs M1	0.7008	0.8897	0.9912	0.9952	0.9960
	M4 vs M1	0.7081	0.8915	0.9919	0.9959	0.9968
	M3 vs M2	0.8135	0.9288	0.9944	0.9963	0.9951
	M4 vs M2	0.8220	0.9307	0.9951	0.9970	0.9960
	M4 vs M3	1.0105	1.0020	1.0008	1.0007	1.0009
		h				
	Models	1	5	22	44	66
Spain	M1	0.0523	0.1074	0.2199	0.2328	0.2672
	M2 vs M1	0.4929	0.9458	1.0013	1.0124	1.0081
	M3 vs M1	0.4023	0.8999	0.9965	1.0112	1.0063
	M4 vs M1	0.4079	0.9018	0.9973	1.0116	1.0066
	M3 vs M2	0.8162	0.9514	0.9952	0.9988	0.9982
	M4 vs M2	0.8276	0.9535	0.9959	0.9992	0.9985
	M4 vs M3	1.0140	1.0022	1.0007	1.0004	1.0003
		h				
	Models	1	5	22	44	66
UK	M1	0.0310	0.0613	0.1360	0.1780	0.1960
	M2 vs M1	0.6671	0.9642	1.0066	1.0030	1.0015
	M3 vs M1	0.5358	0.8754	0.9746	0.9878	0.9909
	M4 vs M1	0.5348	0.8777	0.9739	0.9877	0.9908
	M3 vs M2	0.8032	0.9078	0.9682	0.9848	0.9894
	M4 vs M2	0.8017	0.9102	0.9676	0.9847	0.9894
	M4 vs M3	0.9981	1.0026	0.9994	0.9999	1.0000
		h				
	Models	1	5	22	44	66
US	M1	0.0181	0.0430	0.1026	0.1415	0.1552
	M2 vs M1	0.5137	0.9230	0.9986	1.0020	1.0015
	M3 vs M1	0.4336	0.8884	0.9960	0.9995	0.9993
	M4 vs M1	0.4296	0.8913	0.9968	1.0000	0.9995
	M3 vs M2	0.8440	0.9625	0.9974	0.9975	0.9978
	M4 vs M2	0.8363	0.9657	0.9982	0.9979	0.9980
	M4 vs M3	0.9908	1.0032	1.0008	1.0004	1.0002

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 <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 7 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.

	Models	*h* 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: Refer to Table 1. M1 involves 12 lags.

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

	Models	*h* 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	0.0000	0.0716	0.4893	0.5605
	M4 vs M2	0.0000	0.0000	0.0668	0.4786	0.5651
	M4 vs M3	0.0639	0.0075	0.2327	0.3876	0.5934
		h				
	Models	1	5	22	44	66
Europe	M2 vs M1	0.0000	0.0000	0.0220	0.0003	0.1325
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0007
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0006
	M3 vs M2	0.0000	0.0000	0.0000	0.0000	0.0001

(*continued on next page*)

Table A3 (*continued*)

		h				
	Models	1	5	22	44	66
	M4 vs M2	0.0000	0.0000	0.0000	0.0000	0.0001
	M4 vs M3	0.0514	0.1193	0.6416	0.1423	0.4052
		h				
	Models	1	5	22	44	66
UK	M2 vs M1	0.0000	0.0000	0.0453	0.2239	0.0635
	M3 vs M1	0.0000	0.0000	0.0000	0.0001	0.0000
	M4 vs M1	0.0000	0.0000	0.0000	0.0001	0.0000
	M3 vs M2	0.0000	0.0000	0.0000	0.0000	0.0001
	M4 vs M2	0.0000	0.0000	0.0000	0.0000	0.0002
	M4 vs M3	0.1853	0.4140	0.6712	0.8969	0.9197
		h				
	Models	1	5	22	44	66
US	M2 vs M1	0.0000	0.0000	0.0000	0.0002	0.0110
	M3 vs M1	0.0000	0.0000	0.0000	0.0000	0.0002
	M4 vs M1	0.0000	0.0000	0.0000	0.0000	0.0002
	M3 vs M2	0.0002	0.0000	0.0002	0.0007	0.0020
	M4 vs M2	0.0001	0.0000	0.0002	0.0007	0.0020
	M4 vs M3	0.9385	0.4449	0.5816	0.4227	0.3323

Note: Refer to Table 1. M1 involves 12 lags.

Data availability

Data will be made available on request.

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