The War in Ukraine inducing Volatility spillover between Germany and Central Europe

Introduction

Question:

Germany, Poland, Hungary and the Czech Republic all experienced a great increase in volatility in their main stock indexes: DAX, WIG, BUX, PX, due to the start of the war in Ukraine. Subsequently, how did this period of increased volatilities caused these countries to influence each other? Did DAX experience an increase in volatility first that then also affected WIG, BUX and PX or is it the other way around?

This study presents new results because it examines volatility spillovers between Germany and Central Europe in the context of a relatively recent event, which is an area that has received little attention in the current literature. Unlike previous studies, which tend to focus on a single methodology, this analysis employs multiple models, such GARCH BEKK, Dynamic Conditional Correlation, the Granger Causality Test, and Forecast Error Variance Decomposition. It provides a detailed overview of how market shocks propagate across these countries, filling an important gap in the study of cross-market volatility dynamics.

The first macroeconomic hypothesis that springs the interest into this analysis is that Germany is the biggest industrial producing economy in the European Union. Up until the war in Ukraine, an economy advantage of Germany was its access to cheap gas from Russia. After the onset of the war in Ukraine and the worsening of the relationship between Russia and the European Union, Germany lost its access to affordable gas. This has caused a spike in volatility in the main German stock market index, DAX, in the period following the beginning of the war. [3] [4]

The European Union countries of Central Europe, especially Poland, Hungary and the Czech Republic are highly dependent of the German economy as Germany is the most important economic partner of each. Economic interdependence between these three countries and Germany is very high.

The second hypothesis is that while Germany is dependent on Russian gas, Poland, Hungary and the Czech Republic are geographically closer to Russia, which can also be a major factor that can increase volatility due to economical and political uncertainty, that can also, in turn, indirectly affect the German economy. [5]

In this project we will examine and quantify the level of interdependence between these countries. We will most importantly be examining the level of volatility spillover of Germany into Poland, Hungary and the Czech Republic and the other way around, caused by the war in Ukraine and also be looking at pairwise volatility spillovers between these countries.

We will use the bivariate BEKK-GARCH model and the DCC model for our analysis, the Granger

Causality test, to determine volatility spillover and Forecast Error Variance Decomposition to quantify the proportion of volatility in each market attributable to shocks in others.

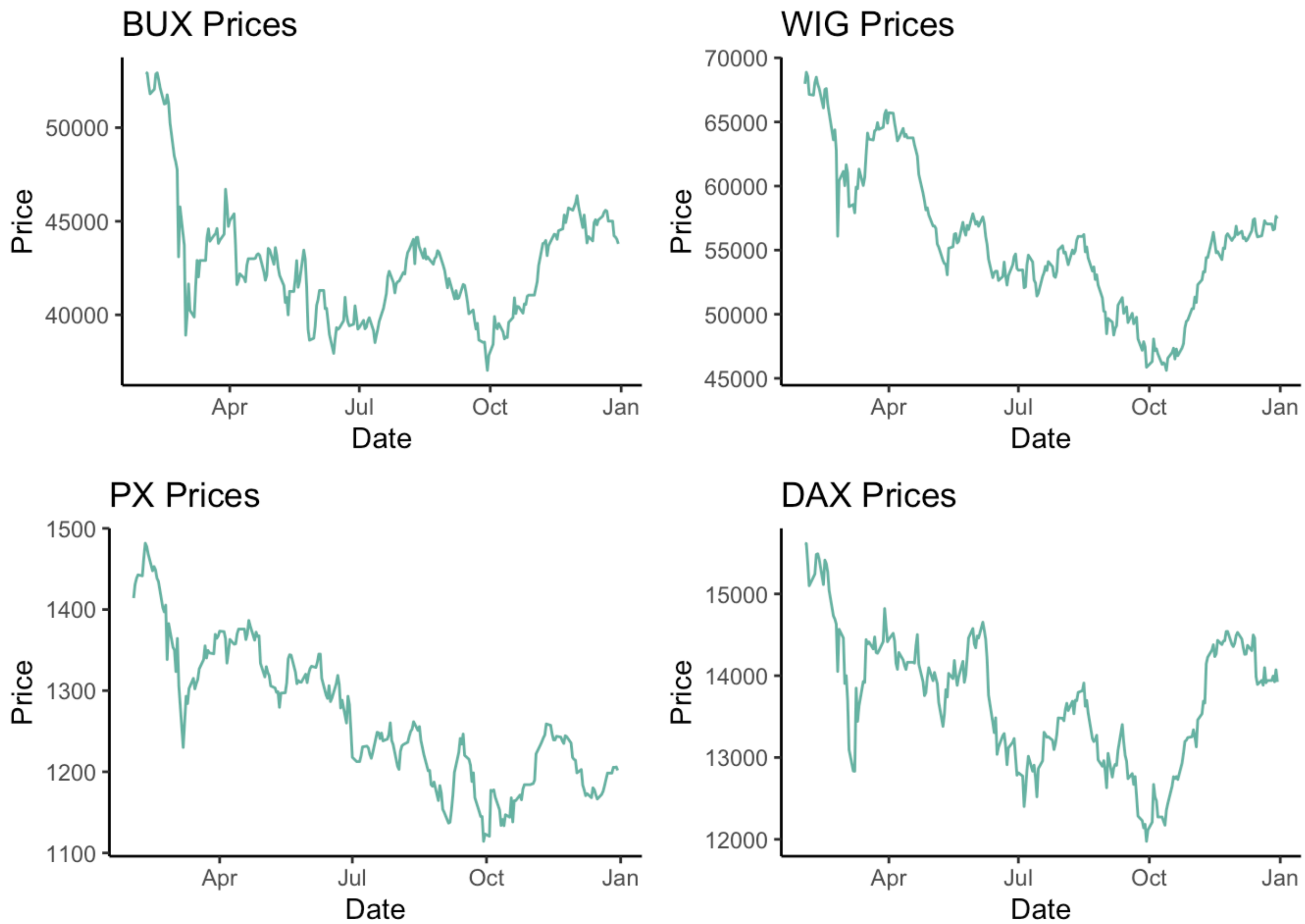
Data

The data was obtain from the platform WRDS and it represents the daily closing prices of the four stock market indices, during the period from 2022-02-01 to 2023-01-01:

European Stock Market Indices

Country	Index
Germany	DAX
Hungary	BUX
Czech Republic	PX
Poland	WIG

It is taken precisely to capture the periods shortly before the onset of the war in Ukraine and the periods characterised by economic uncertainty, which include sanctions and war worries, after the onset of the war.



From late February 2022 until January 2023, these price plots for BUX (Hungary), WIG (Poland), PX (Czech Republic), and DAX (Germany) reflect how the outbreak of war in Ukraine triggered a swift sell off as BUX immediately plunged from 50,000 to below 40,000, WIG went from 70,000 to nearly 50,000 after which markets partially recovered or stabilized in anticipation of policy responses. Notably, regional indices like BUX and WIG remained more volatile due to geopolitical and currency risk, while DAX prices oscillated but seemed slightly less extreme.

When converted into returns, the data reveal occasional spikes whenever market sentiment rapidly shifted, reflecting macroeconomic events generally regarding energy shortages, inflation prints, or NATO developments.

Summary Statistics of the Return Series

	r_wig	**r_px**	**r_bux**	**r_dax**
Mean	-0.000764	-0.000737	-0.000798	-0.000483
Variance	0.000296	0.000166	0.000381	0.000217
Skewness	-0.771***	-0.474***	-1.337***	0.440***
	(0.000)	(0.003)	(0.000)	(0.006)
Kurtosis	7.952***	3.133***	7.764***	2.982***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	647.845***	105.788***	665.814***	95.441***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-5.813***	-5.275***	-4.197***	-2.781***
	(0.000)	(0.000)	(0.000)	(0.006)
Q(20)	45.027***	27.183***	39.704***	25.330***
	(0.000)	(0.001)	(0.000)	(0.001)
Q2(20)	45.683***	93.118***	138.082***	52.986***
	(0.000)	(0.000)	(0.000)	(0.000)

The return series for Central European indices (WIG-Poland, PX-Czech Republic, BUX-Hungary) and Germany's DAX reflect heightened market stress amid the Russia-Ukraine war. All indices exhibited slightly negative mean returns (-0.0005 to -0.0008), signaling overall downward pressure, with BUX and WIG showing the weakest performance. Volatility was highest in BUX (variance=0.00038) and WIG (0.00030), likely due to their geographic proximity to the conflict, while DAX (0.00022) and PX (0.00017) were relatively more stable. Skewness highlights asymmetry: BUX, WIG, and PX had fat left tails, whereas DAX leaned toward positive outliers. Kurtosis values confirmed fat-tailed distributions, especially in WIG (7.95) and BUX (7.76), indicating frequent extreme moves. Jarque-Bera tests overwhelmingly rejected normality (JB=665.8 for BUX), and stationarity was confirmed by significant ERS statistics. Strong $Q^2(20)$

results (138.1 for BUX) revealed pronounced volatility clustering, validating the use of GARCH models. These findings show that Central Europe is vulnerable to geopolitical shocks, as opposed to DAX.

Empirical Analysis

The analysis was conducted in **R** using the `mgarchBEKK` and `rmgarch` libraries for BEKK-GARCH and DCC-GARCH modeling, alongside `vars` for spillover index calculations. These tools were chosen for their robustness in handling financial time series and modeling volatility dynamics during crises.

- **BEKK-GARCH(1,1)**: Captures asymmetric volatility spillovers between DAX (Germany) and Central European indices (WIG, BUX, PX), explicitly modeling how shocks transmit across markets. BEKK captures cross-market spillovers critical for Germany's influence on Central Europe.
- **DCC-GARCH**: Tracks time-varying correlations, essential for understanding evolving interdependencies under stress as well as crisis-driven correlation shifts without restrictive assumptions. A multivariate Student's t-distribution addressed fat-tailed returns, with dynamic correlations governed by shock (α) and persistence (β) parameters.
- **Data Preprocessing**: Daily returns (Feb 2022–Jan 2023) were standardized (mean=0, variance=1) and scaled for stability of optimisation.
- **Spillover Index**: A 150-day rolling window with VAR(2) and 10-step-ahead FEVD quantified directional and net spillovers. [2]
- **Residuals**: Near-zero means and variances ≈1.
- **Stationarity**: Eigenvalues <1 (BEKK) and positive ERS tests.
- **Robustness**: Consistent results across VAR lags (1–3) and forecast horizons.

As such, this methodology combines BEKK-GARCH for direct spillovers, DCC-GARCH for dynamic correlations, and FEVD-based spillover indices to analyze DAX's role as a volatility transmitter.

Results

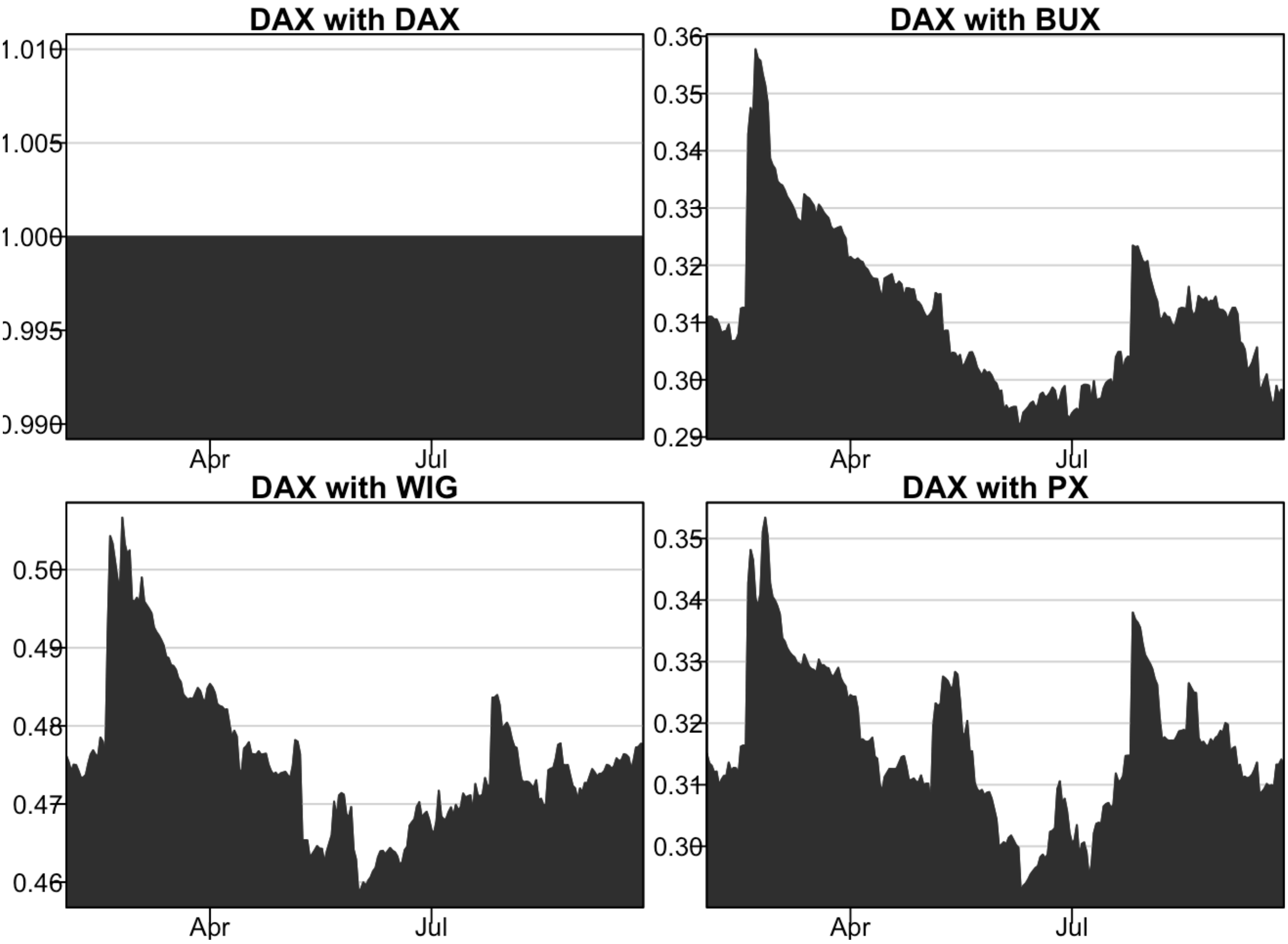
DCC Spillover

DCC-GARCH Parameter Estimates

DCC-GARCH Parameter Estimates

	Estimate	Std. Error	t value	Pr(> |t|)
[DAX].mu	0.88000268	0.06292269	13.98545916	0.00000000
[DAX].alpha1	0.00000002	0.00011678	0.00014532	0.99988405
[DAX].beta1	0.99747038	0.00015426	6466.18339709	0.00000000
[DAX].shape	4.52646621	0.92805375	4.87737507	0.00000108
[BUX].mu	0.99960620	0.09626296	10.38412061	0.00000000
[BUX].alpha1	0.09492686	0.20236274	0.46909258	0.63900347
[BUX].beta1	0.90407314	0.18931846	4.77540937	0.00000179
[BUX].shape	4.47213784	2.17159324	2.05938100	0.03945775
[WIG].mu	1.06370941	0.07123666	14.93205125	0.00000000
[WIG].alpha1	0.00000000	0.00012320	0.00000670	0.99999466
[WIG].beta1	0.99743491	0.00017057	5847.71255718	0.00000000
[WIG].shape	4.58163576	0.97751776	4.68701023	0.00000277
[PX].mu	0.62560669	0.07784447	8.03662319	0.00000000
[PX].alpha1	0.11198074	0.05763408	1.94296058	0.05202092
[PX].beta1	0.88701925	0.05771406	15.36920683	0.00000000
[PX].shape	3.82273645	0.98162331	3.89430079	0.00009848
[Joint]dcca1	0.00268547	0.00510743	0.52579745	0.59902895
[Joint]dccb1	0.96570524	0.00718844	134.34138999	0.00000000
[Joint]mshape	5.90966537	0.77473992	7.62793448	0.00000000

The DCC-GARCH model highlights distinct volatility dynamics across the indices. DAX (Germany) and WIG (Poland) exhibit near-zero short-term shock sensitivity (ARCH $\alpha1 \approx 0.000$), indicating their volatility is driven by long-term persistence (GARCH $\beta1 \approx 0.997$). In contrast, BUX (Hungary) and PX (Czech Republic) show higher sensitivity to recent shocks ($\alpha1 = 0.095$ and 0.112, respectively), though volatility decays faster ($\beta1 = 0.904$ and 0.887). All markets exhibit heavy tailed return distributions (shape <5), with PX (shape=3.82) most prone to extreme swings. Mean returns are positive, led by WIG (+1.06), reflecting regional growth trends. While DAX/WIG volatility is dominated by persistence, BUX/PX face sharper short-term reactions to events like geopolitical crises.



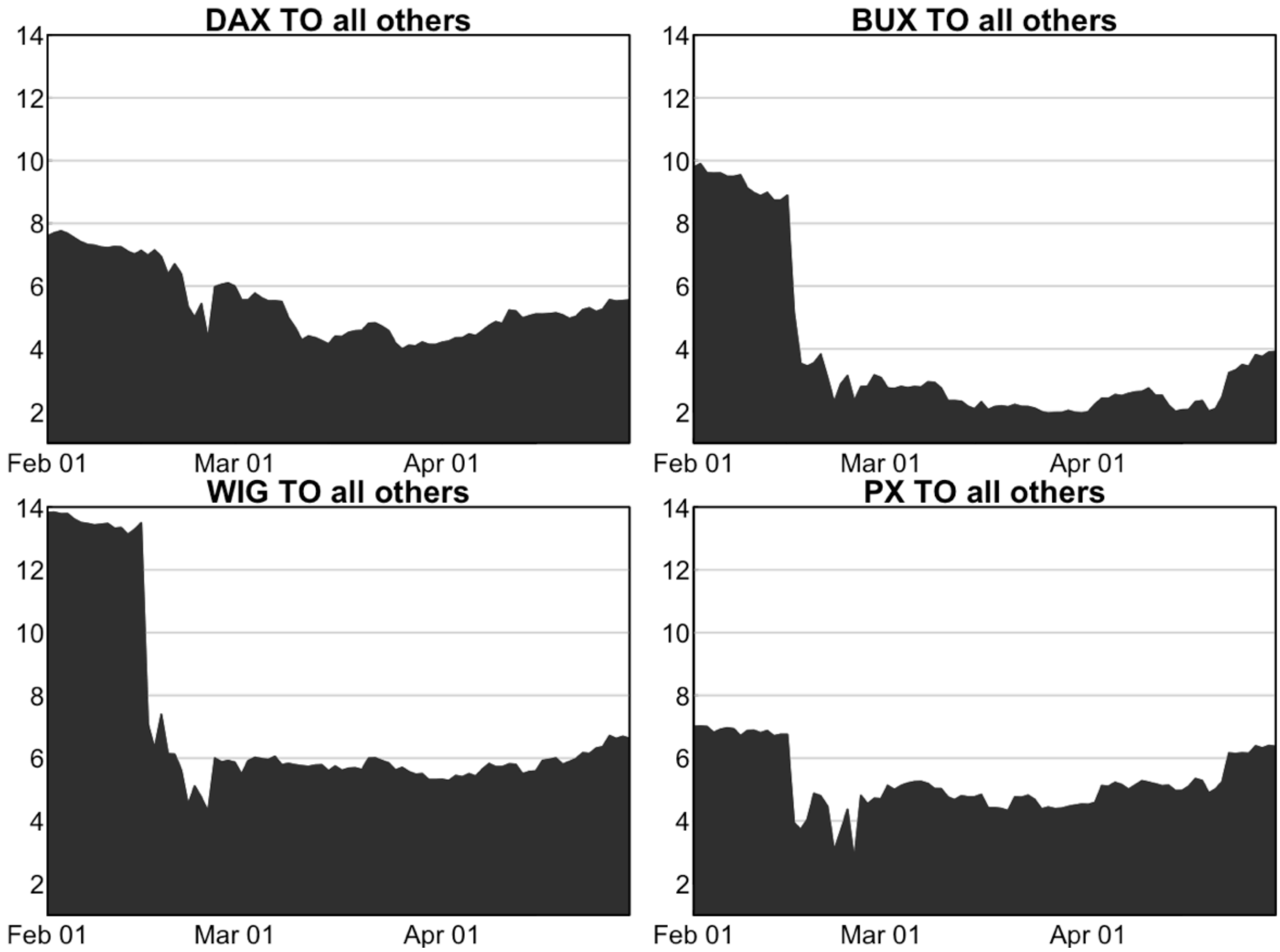
These conditional correlations reflect how Russia's invasion of Ukraine affected Central and Eastern European markets, with Germany's DAX serving as a large, highly liquid reference market. The DAX–DAX panel simply illustrates that the model's scale for Germany's own volatility sits near unity (around 1.0) throughout; small fluctuations above/below 1.0 usually stem from how the conditional covariance is parameterized or scaled in the model.

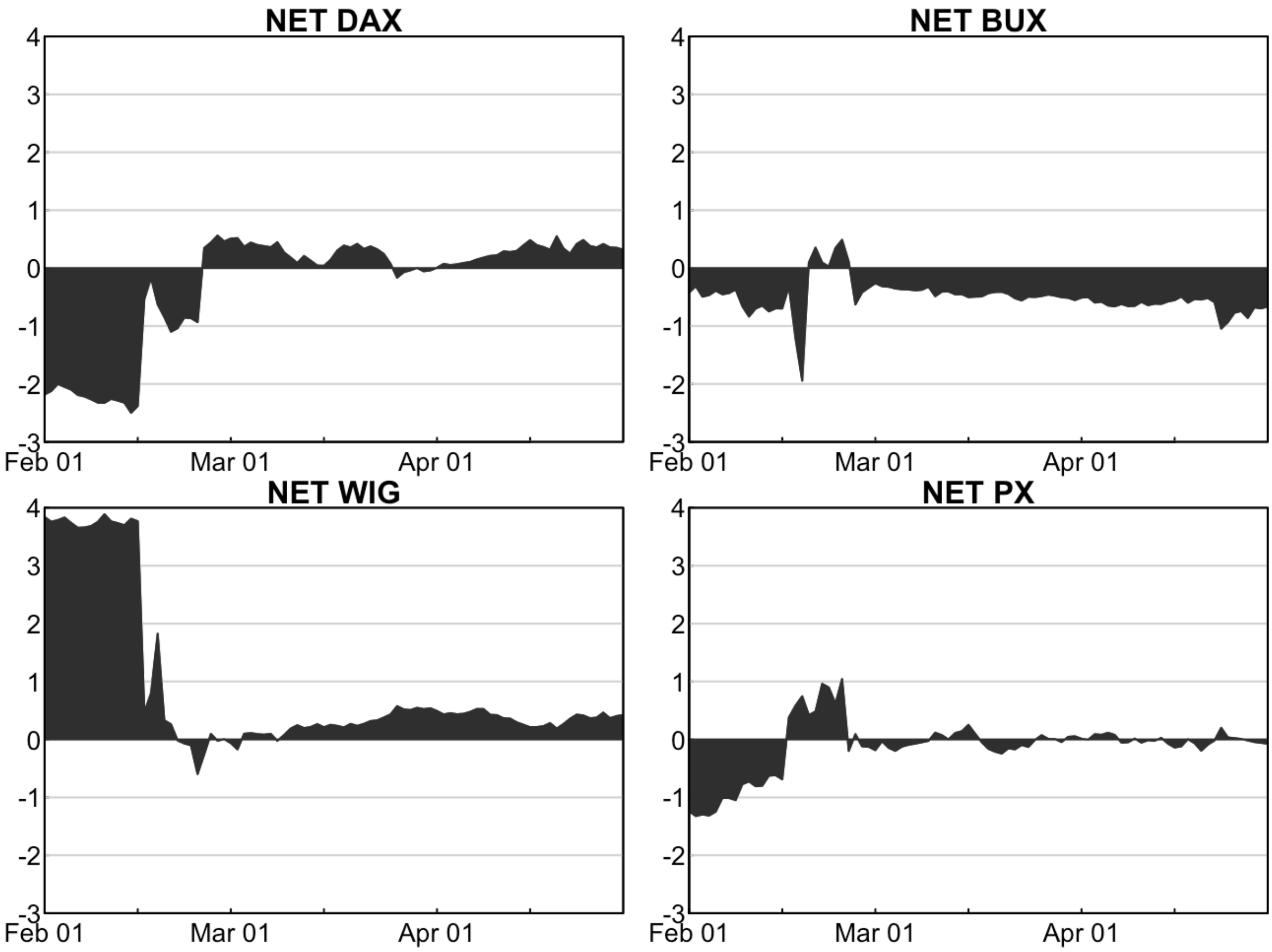
More revealing are the DAX–BUX, DAX–WIG, and DAX–PX correlations. In the early weeks of the invasion, all three markets faced heightened uncertainty, spiking their co-movement with Germany and each other. This pattern suggests that once markets priced in the war's initial shock, and realized Hungary's unique political stance and Russian energy reliance, the correlation fell somewhat. [9]

Poland's WIG, due to its geographic proximity and significant refugee influx, initially shows the largest correlation with DAX (peaking around 0.56). As the conflict unfolded and local risks grew more idiosyncratic (government debt measures, inflation), DAX–WIG correlation gradually declined toward the mid-0.40s by mid year. This shows that while the region's markets moved together under the first wave of war-driven volatility, they later diverged as investors differentiated Poland's geopolitical risk from Germany's broader EU-centric risk.

The Czech market exhibits a similar but slightly lower correlation range with DAX. This suggests that although the Czech Republic also faces supply-chain disruptions and energy challenges, its equity market is smaller and less internationally traded than the DAX or the WIG. Hence, outside investors tend to reassess correlations once the immediate shock fades, leading to a drop in co-movement as local fundamentals dominate. [10]

Overall, the early spikes in correlation across the board highlight the risk-off period when the conflict first broke out and investors rapidly re-priced the entire region. Over subsequent months, correlations receded as country-specific factors took hold.





The top row of charts illustrates how much volatility each index exports to the others. For instance, “DAX TO all others” starts around 6–8%, dips in early March (to roughly 4%), and then rebounds toward 5–6% by April, signaling that Germany’s DAX consistently influences its Central/Eastern European counterparts. The Hungarian BUX index begins near 10%, drops sharply below 2% around late February/early March, and recovers to about 4–5%. Poland’s WIG starts very high (12–14%), falls toward 5% in early March, suggesting that it was initially the largest transmitter of volatility (likely due to proximity to the war). The Czech PX moves from ~6% down to about 3–4% and then climbs to near 5–6% again, which show a temporary dip in its spillover effect.

The bottom row, measures the difference between how much each market contributes versus how much it receives. A positive net value implies the market is a net transmitter, while a negative value indicates a net receiver. Early on, DAX sits at around –2 (net receiving), but gradually crosses above zero and settles near +1, implying it evolved into a net transmitter. BUX plunges below –2 in early March before returning closer to zero, which means it shifted from moderate transmitter to net receiver. WIG starts near +4, rapidly drops to around zero. PX stays near zero or slightly negative early on, spikes above +1 in March, then returns near zero.

Granger Causality Test

Model	F-Statistic	p-Value	Significance	Interpretation
WIG ~ DAX	3.93328	0.0091759	** (p < 0.01)	Granger causality exists from DAX to WIG
BUX ~ DAX	0.09351	0.9635700	Not significant	No Granger causality from DAX to BUX
PX ~ DAX	2.13251	0.0968890	. (p < 0.10)	Weak evidence of Granger causality from DAX to PX

The Granger causality test reveals that there is statistically significant evidence of causality from DAX to WIG, indicating that past values of DAX help predict WIG returns. This suggests that Germany's economic developments have an influential impact on Poland's stock market. There is no significant evidence of Granger causality from DAX to BUX, suggesting that Hungary's market movements are more independent or driven by different factors. There is weak evidence of Granger causality from DAX to PX.

BEKK implementation

BEKK Model Diagnostics

Parameter	Value
Number of estimated series	474
Length of estimated series	237
Estimation Time	0.4615
Total Time	0.4713
BEKK Order	1 1
AIC	-1305.46
Eigenvalue 1	0.4723
Eigenvalue 2	0.2218
Eigenvalue 3	0.0109
Eigenvalue 4	0.0063
Unconditional Covariance (1,1)	0.00024392789
Unconditional Covariance (1,2)	0.00012491454
Unconditional Covariance (2,2)	0.00037960014
Variance of Residuals (1)	0.99536367
Mean of Residuals (1)	-0.010196098
Variance of Residuals (2)	1.0017018
Mean of Residuals (2)	-0.028750347

The BEKK-GARCH(1,1) analysis reveals effective modeling of volatility spillovers and interdependencies between two financial series, supported by a sufficiently large dataset (474 series, 237 periods) and rapid convergence (0.47 seconds). The model's stationarity (eigenvalues <1) and strong fit (AIC = -1305.46) ensure reliable long-term volatility forecasts. Unconditional covariances indicate moderate long-term co-movement, while residual statistics (variances near 1, near-zero means) confirm minimal unexplained volatility. The results highlight persistent volatility transmission and spillover risks, crucial for managing interconnected markets during crises like the Ukraine war, with applications in dynamic risk assessment and portfolio strategy. [6]

C Matrix Estimates

Parameter	Estimate	Standard.Error
C (1,1)	0.01263417	0.00097142
C (1,2)	0.00727160	0.00176203
C (2,2)	0.01123618	0.00385117

The C matrix estimates in the BEKK-GARCH model, representing baseline long-term volatility and covariance components, show small magnitudes with low standard errors, indicating precise estimates. These values suggest minimal inherent volatility, as most market fluctuations are driven by dynamic factors like shocks (ARCH effects) and volatility persistence (GARCH effects).

ARCH Matrix Estimates

Parameter	Estimate	Standard.Error
ARCH (1,1)	0.04449591	0.09582555
ARCH (1,2)	0.02933124	0.14106316
ARCH (2,1)	0.38902142	0.10688349
ARCH (2,2)	0.53259233	0.14765856

- **ARCH (1,1) = 0.0445** (SE=0.0958) indicates limited self-reaction to past shocks in the first market (e.g., Germany), suggesting reliance on long-term volatility persistence rather than immediate shocks.
- **ARCH (1,2) = 0.0293** (SE=0.1411) shows weak spillovers from the second market to the first, implying minimal short-term external influence.
- **ARCH (2,1) = 0.3890** (SE=0.1069) highlights strong volatility transmission from the first market to the second (e.g., Central Europe), reflecting regional dependency on external shocks during crises like the Ukraine war.
- **ARCH (2,2) = 0.5326** (SE=0.1477) shows significant internal volatility clustering in the second market, driven by its own past shocks.

The results emphasize asymmetric spillovers, with the second market more reactive to external shocks than vice versa.

GARCH Matrix Estimates

Parameter	Estimate	Standard.Error
GARCH (1,1)	-0.10789665	0.11635894
GARCH (1,2)	0.49689354	0.50875593
GARCH (2,1)	-0.02118613	0.06751858
GARCH (2,2)	0.10998657	0.12568488

The GARCH matrix estimates in the BEKK model highlight asymmetric long-term volatility dynamics and spillovers between the two markets:

- **GARCH (1,1) = -0.1079** (SE=0.1164): The unusual negative value for the first market's volatility persistence suggests potential mean reversion, where shocks fade quickly rather than persisting.
- **GARCH (1,2) = 0.4969** (SE=0.5088): A positive spillover from the second market to the first implies prolonged volatility in the second market amplifies long-term volatility in the first (Germany reacting to Central European instability).
- **GARCH (2,1) = -0.0212** (SE=0.0675): Minimal reverse spillovers from the first to the second market, suggesting limited long-term influence from the first market's volatility.
- **GARCH (2,2) = 0.1100** (SE=0.1257): Moderate persistence in the second market's volatility, though lower than typical GARCH values, indicating faster decay of shocks.

Analysis

For the DCC model we have distinct volatility dynamics across DAX, WIG, BUX, and PX, driven by varying sensitivities to shocks and persistence levels. DAX and WIG show near zero short-term shock sensitivity but exhibit strong long-term persistence . Their fat-tailed distributions (shape ~4.5) indicate elevated crash risks compared to normal markets. In contrast, BUX and PX are more reactive to recent shocks (α_1 = 0.095–0.112) but experience faster volatility decay (β_1 = 0.887–0.904), with PX (shape = 3.82) particularly vulnerable to extreme swings due to its smaller market size. During the initial shock (Feb–Mar 2022), DAX-BUX correlations spiked to >0.35, DAX-WIG peaked at ~0.56 (driven by Poland's proximity to Ukraine), and DAX-PX reached ~0.35 due to Czechia's energy dependence. By mid-2022, correlations diverged—BUX declined to ~0.29–0.31, WIG stabilized near 0.40–0.45 amid local risks like inflation and refugee inflows, and PX remained lower (~0.30) due to its domestic market structure. DAX acted as a net volatility transmitter, with 30–40% of BUX, WIG, and PX volatility explained by DAX shocks post-invasion. A 1% volatility shock in DAX/WIG retains ~74% impact after 100 days, while BUX/PX retain only

~12%, reflecting their quicker stabilization. Consequently, hedging DAX and WIG requires long-term instruments like variance swaps, while short-dated options are more effective for event-driven risks in BUX and PX. Portfolio diversification during crises must account for the initial co-movement captured by DCC models and the subsequent fragmentation into country specific risks, balancing long tail hedging strategies with flexible, short-term protections. [7]

The BEKK model illustrates short-term shocks in Germany's DAX strongly propagate to Central European markets (ARCH(2,1)=0.389), reflecting immediate spillovers caused by the war. However, DAX's own volatility shows limited persistence (GARCH(1,1)= -0.1079), suggesting shocks fade quickly. In the long term, DAX has minimal influence on Central Europe (GARCH(2,1)= -0.0212), indicating its volatility does not persistently destabilize regional markets.
Central European markets exert weak short-term spillovers on DAX (ARCH(1,2)=0.0293), but prolonged regional volatility amplifies DAX's long-term instability (GARCH(1,2)=0.4969). Central Europe's internal volatility clustering (ARCH(2,2)=0.5326) and moderate persistence (GARCH(2,2)=0.1100) highlight their sensitivity to local shocks, which indirectly affect DAX over time.
The relationship is asymmetric: Central Europe is a short-term receiver of DAX shocks, while its own turbulence has delayed, uncertain long-term effects on Germany. This outlines DAX's role as a regional volatility driver during crises, while Central Europe's risks require monitoring for sustained impacts. Investors should prioritise hedging against DAX driven short-term swings but remain cautious about prolonged regional instability spilling back into German markets. [8]

Conclusion

This study confirms that DAX is a significant volatility transmitter to Central European markets, particularly WIG and BUX. DAX explains 30–40% of volatility in these markets after the onset of the war, with strong Granger causality from DAX to WIG and moderate influence on PX. Initial volatility spillovers peaked in early 2022, driven by geopolitical risks. BUX and PX exhibited faster volatility decay, while WIG remained more persistently affected by DAX shocks. These results suggest that Germany's market plays a dominant role in regional volatility propagation, necessitating tailored hedging strategies for each country.

Bibliography

[1] J., Caporale, G.M., Schulze-Ghattas, M. and Spagnolo, N. (2013). Volatility Spillovers and Contagion from Mature to Emerging Stock Markets. *Review of International Economics*, 21(5), pp.1060–1075. doi:https://doi.org/10.1111/roie.12091.

@10.1002/ijfe.2717.

[2] (2020). -measuring-volatility-spillovers/1_summary.r at master · sardormirzaev/-measuring-volatility-spillovers. [online] GitHub. Available at: https://github.com/sardormirzaev/-measuring-

volatility-spillovers/blob/master/1_summary.r

[3] Aliu, F., Mulaj, I. and Hašková, S. (2023). Consequences of the Russia-Ukraine war: evidence from DAX, ATX, and FTSEMIB. *Studies in Economics and Finance*. doi:https://doi.org/10.1108/sef-12-2022-0555.

[4] Clean Energy Wire. (2022). *War in Ukraine: Tracking the impacts on German energy and climate policy*. [online] Available at: https://www.cleanenergywire.org/news/ukraine-war-tracking-impacts-german-energy-and-climate-policy[Accessed 1 Feb. 2025].

[5] Deininger.com. (2024). *Deininger – Germany and the CEE Region: A Strategic Partnership*. [online] Available at: https://www.deininger.com/en/post/deutschland-und-mittel-und-osteuropa-eine-strategische-partnerschaft-fur-das-wirtschaftswachstum-in-europa[Accessed 1 Feb. 2025].

[6]cran (2016). *mgarchBEKK/R/BEKK.R at master · cran/mgarchBEKK*. [online] GitHub. Available at: https://github.com/cran/mgarchBEKK/blob/master/R/BEKK.R [Accessed 1 Feb. 2025].

[7] Ugurlu, E., Thalassinos, E. and Muratoglu, Y. (2014). Modeling Volatility in the Stock Markets using GARCH Models: European Emerging Economies and Turkey. *International Journal of Economics and Business Administration*, [online] II(Issue 3), pp.72–87. doi:https://doi.org/10.35808/ijeba/49.

[8] Beirne, J., Caporale, G.M., Schulze-Ghattas, M. and Spagnolo, N. (2013). Volatility Spillovers and Contagion from Mature to Emerging Stock Markets. *Review of International Economics*, 21(5), pp.1060–1075. doi:https://doi.org/10.1111/roie.12091.

[9] Gheorghe, C. and Oana Panazan (2023). Effects of information related to the Russia-Ukraine conflict on stock volatility: An EGARCH approach. *Cogent economics & finance*, 11(2). doi:https://doi.org/10.1080/23322039.2023.2241205.

[10] Živkov, D., Njegić, J. and Milenković, I. (n.d.). INTERRELATIONSHIP BETWEEN DAX INDEX AND FOUR LARGEST EASTERN EUROPEAN STOCK MARKETS. *Romanian Journal of Economic Forecasting -XXI*, [online] (3), p.2018. Available at: https://ipe.ro/rjef/rjef3_18/rjef3_2018p88-103.pdf [Accessed 1 Feb. 2025].