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Evolving Economic Relationships: A TVP-VAR Analysis of Trade, World Uncertainty, and Stock Market Volatility in Europe

Abstract. *Understanding the intricate relationship between trade, uncertainty, and stock market volatility is fundamental to navigating economic fluctuations. This paper aims to examine the dynamic interdependencies between international trade, world uncertainty, and stock market volatility in 15 European countries using a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. After extracting time-varying coefficients, we employ a Dynamic Factor Model (DFM) to identify common factors driving these dynamics. Our findings highlight significant patterns influenced by major economic events such as the European debt crisis, Brexit, and the COVID-19 pandemic and provide practical implications for better anticipation and response to economic shifts. This enhances economic stability and growth and fosters a more informed and enlightened approach to economic policy-making.*

Keywords: *economic uncertainty, international trade, stock market volatility, dynamic factor models, economic events.*

JEL Classification: F14, D80, F30.

1. Introduction

The relationship between international trade, global uncertainty, and stock market volatility is nodal for economists and policymakers. Understanding this nexus helps predict economic shifts and formulate effective policies. International trade is central to economic activity, while global uncertainty involves key political

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and economic events that can disrupt trade and economic stability. Stock market volatility reflects investor sentiment, often reacting to changes in trade policies and economic conditions. This interplay requires sophisticated analysis to identify underlying patterns, enabling better policy design and risk management strategies for businesses and investors.

At a broader level, the interconnection between these variables significantly affects financial stability and economic growth. Trade disruptions from world uncertainty can lead to supply chain issues, impacting production and employment. Similarly, stock market volatility can influence consumer confidence and spending, affecting economic activity. In an increasingly interconnected world, the ripple effects of global uncertainty and market volatility in one country can quickly spread to others through trade and financial linkages. Understanding these dynamics is crucial to anticipate and mitigate global economic shocks.

This study uses a time-varying parameter vector autoregression (TVP-VAR) model to analyse the relationships between international trade, global uncertainty, and stock market volatility in 15 European countries. This model captures how these relationships evolve. The analysis focuses on extracting coefficients from the TVP-VAR model to identify common patterns and unique country-specific dynamics. A Dynamic Factor Model (DFM) is then applied to these coefficients to uncover shared influences and trends. Finally, the common factors are decomposed into trend, seasonality, and cycle components, providing insights into the long-term, periodic, and irregular fluctuations affecting these economic variables. This analysis offers crucial insights into the interplay of key economic factors across Europe, informing economic policy and investment strategies.

2. Literature review

This section reviews the main studies and theoretical frameworks to improve our understanding of the interrelationship between international trade, uncertainty, and stock market volatility. It provides the context for the analytical approaches employed in this paper. International trade is a key driver of economic growth and development. World uncertainty, characterised by unpredictable government policies, geopolitical tensions, and institutional instability, can significantly disrupt economic activities. Theoretical frameworks such as the Policy Uncertainty Theory posit that uncertainty about future policies can delay investment and consumption decisions, leading to economic slowdowns (Bernanke, 1983). Empirical studies have found that higher levels of uncertainty usually correlate with lower levels of investment, reduced trade flows, and increased market volatility, as demonstrated by Bloom (2009) and Julio & Yook (2012). Stock market volatility reflects investors' collective sentiment concerning future economic conditions. It is a barometer of economic stability and is influenced by many factors, including macroeconomic indicators, corporate earnings, and geopolitical events. The Efficient Market Hypothesis (Fama, 1970) suggests that stock prices fully reflect all available information, implying that volatility responds to new information on the market.

However, behavioural finance theories argue that psychological factors and irrational behaviour can also drive market volatility (Shiller, 2000).

The interaction between international trade, uncertainty, and stock market volatility is multifaceted and dynamic. Several studies have explored how these variables influence each other. For instance, periods of heightened uncertainty induced by government policy are often associated with increased stock market volatility and disruptions in trade flows (Pástor & Veronesi, 2012). In contrast, stable political environments support robust trade relationships and predictable market conditions. As mentioned by Škrinjarić et al. (2021), the relationship between stock market returns and exchange rates (which impact trade by altering the relative prices of exports and imports) presents valuable insights for policymakers and investors. Fernández-Rodríguez & Sosvilla-Rivero (2020) examines volatility spillovers between stock and foreign exchange markets, finding significant short-run interactions, particularly during financial crises. Their results show that stock markets mainly drove volatility during specific crises, whereas foreign exchange markets dominated in others. These results highlight again the interconnectedness and dynamic nature of volatility between these markets, especially during periods of economic instability.

Albu et al. (2015) analysed asymmetric volatilities across European stock markets and identified industries associated with risk in the European stock market. Supplementary, economic uncertainty measures have significant predictive power for the realised volatility of commodity futures returns, surpassing the explanatory capacity of lagged volatility, returns, trading activities, and hedging pressures (Watugala, 2019).

Time-varying parameter (TVP) models have gained popularity as effective tools for capturing the dynamic nature of economic relationships. These models allow parameters to change over time, allowing for a more accurate reflection of the dynamic and complex nature of economic relationships and their impacts over different periods. This adaptability highlights the shifting nature of economic relationships, making these models valuable tools for understanding complex economic systems (Primiceri, 2005). This is also helpful in examining the volatility spillover of stock markets (Chirilă & Chirilă, 2022). TVP models are particularly advantageous for analysing the effects of economic policies, financial crises, and structural changes on macroeconomic indicators.

As acknowledged in the literature, DFMs are employed to extract common factors from a large set of variables, summarising the underlying drivers of economic dynamics (Stock & Watson, 2002). They effectively identify common trends and co-movements across countries or regions. They are frequently utilised in macroeconomic forecasting and analysing the transmission of economic shocks, providing valuable insights into the interconnectedness of global economies. (Forni et al., 2000).

Decomposing time series data into trend, seasonal, and cyclical components enhances understanding of the underlying patterns. These decomposition techniques isolate long-term trends from short-term fluctuations and irregular variations, facilitating a more nuanced analysis of economic dynamics. This detailed breakdown allows researchers to discern the persistent factors driving economic changes and to distinguish them from temporary and irregular influences, thereby enabling more precise and insightful economic analysis (Cleveland et al., 1990). Various economic indicators have been analysed using these methods to study business cycles, seasonal effects, and structural changes (Harvey, 1990).

3. Model specification

3.1 Data Description

This section presents the data used in our analysis, encompassing international trade data, world uncertainty data, and stock market volatility data for 15 European countries from January 2008 to December 2023. The international trade data includes net trade values (exports minus imports) for the 15 countries. This data provides insights into these countries' trade activities and economic interdependencies. The descriptive statistics indicate significant variability in trade balances across different countries and periods, highlighting the dynamic nature of European international trade.

We utilise monthly uncertainty indices from the Economic Policy Uncertainty platform, which are derived from the frequency counts of the term "uncertainty" (including its variants) in the quarterly Economist Intelligence Unit (EIU) country reports. These reports cover each country's significant political and economic events, providing analysis and forecasts of political, policy, and economic conditions. Country-specific analyst teams and a central EIU editorial team produce them. To ensure comparability across countries, the raw counts are normalised by the total word count of each report. We notice substantial fluctuations in political uncertainty, with some countries experiencing higher average levels of uncertainty than others, suggesting differing political environments and risks.

Based on a GARCH (1,1) model on daily log-returns, stock market volatility data measures market uncertainty and investor sentiment. As previously shown, the greater volatility in benchmark indices provides explanatory power for economic sentiment indices (Lupu et al., 2016). This data helps us understand the impact of market volatility on trade and political uncertainty. The descriptive statistics show considerable variation in volatility levels across countries, indicating diverse market conditions and investor behaviour.

3.2 Time-Varying Parameter Vector Autoregression

To capture the evolving dynamics between international trade, political uncertainty, and stock market volatility across 15 European countries, we employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. The TVP-VAR model allows the relationships between variables to change over time, reflecting the dynamic nature of economic interactions and described by (Chan &

Jeliazkov, 2009). TVP-VAR models were previously implemented to analyse the influence of cryptocurrency uncertainty indices on green bond markets, currency exchanges, and commodity trading systems (Batra et al., 2025), to evaluate the static and dynamic interrelationships among DeFi, G7 banking systems, and equity markets, with particular attention to pivotal events like the COVID-19 pandemic, the cryptocurrency surge, and the Russia-Ukraine conflict (Younis et al., 2024) or the influence of global uncertainties on market interconnections and spillover effects (Liu et al., 2024).

The general form of the VAR model can be written as follows:

$$\boldsymbol{Y}_t = \boldsymbol{A}_0 + \boldsymbol{A}_1\boldsymbol{Y}_{t-1} + \boldsymbol{A}_2\boldsymbol{Y}_{t-2} + \cdots + \boldsymbol{A}_p\boldsymbol{Y}_{t-p} + \boldsymbol{u}_t$$

where $\boldsymbol{Y}_t$ is a $k \times 1$ vector of endogenous variables, $\boldsymbol{A}_0$ is a $k \times 1$ vector of intercept terms, $\boldsymbol{A}_i$ $(for i = 1, \dots, p)$ are $k \times k$ matrices of coefficients, and $\boldsymbol{u}_t$ is a $k \times 1$ vector of error terms.

In the TVP-VAR model, the coefficients $\boldsymbol{A}_i$ are allowed to change over time. The model can be specified as:

$$\boldsymbol{Y}_t = \boldsymbol{A}_0(t) + \boldsymbol{A}_1(t)\boldsymbol{Y}_{t-1} + \boldsymbol{A}_2(t)\boldsymbol{Y}_{t-2} + \cdots + \boldsymbol{A}_p(t)\boldsymbol{Y}_{t-p} + \boldsymbol{u}_t$$

where $\boldsymbol{A}_i(t)$ represents the time-varying coefficients.

For our analysis, we use a TVP-VAR model with one lag ($p = 1$), capturing the immediate past influences. The model can be written as:

$$\boldsymbol{Y}_t = \boldsymbol{A}_0(t) + \boldsymbol{A}_1(t)\boldsymbol{Y}_{t-1} + \boldsymbol{u}_t$$

where:

- $\boldsymbol{Y_t} = \begin{pmatrix} Trade_t \\ Uncertainty_t \\ Volatility_t \end{pmatrix}$ is the vector of endogenous variables for trade, political uncertainty, and stock market volatility at time t,
- $\boldsymbol{A}_0(t)$ is the time-varying intercept vector,
- $\boldsymbol{A}_1(t)$ is the time-varying coefficient matrix for the lagged variables.

The TVP-VAR model estimation uses state-space representation and the Kalman filter to update the coefficients over time. It is reformulated in a state-space form to facilitate the estimation of time-varying parameters. The state-space representation consists of two equations: the observation equation and the state equation. The observation equation is the following:

$$\boldsymbol{Y}_t = \boldsymbol{Z}_t\alpha_t + \boldsymbol{u}_t$$

where:

- $\boldsymbol{Y}_t$ is the $k \times 1$ vector of observed variables,
- $\boldsymbol{Z}_t$ is the $k \times m$ design matrix, where $m = k(k+1)$,

- α_t is the $m \times 1$ state vector containing the time-varying coefficients,
- $\boldsymbol{u}_t \sim \mathcal{N}(0, \boldsymbol{R})$ is the observation noise.

The following equation is the state equation:

$$\alpha_t = \boldsymbol{T}\alpha_{t-1} + \eta_t$$

where:
- $\boldsymbol{T}$ is the $m \times m$ transition matrix (typically an identity matrix for TVP-VAR),
- $\eta_t \sim \mathcal{N}(0, \boldsymbol{Q})$ is the state noise.

The initial state vector α_1 is assumed to follow a normal distribution with mean a_1 and covariance $\boldsymbol{P}_1$.

The estimation of the TVP-VAR model is threefold. It involves the initialisation process, in which we set starting values for the state vector α_1 and its covariance matrix $\boldsymbol{P}_1$; the second step consists of the use of the Kalman filter to update the state vector recursively α_t and its covariance matrix $\boldsymbol{P}_t$ for each period t, while the third stage covers the estimation of the hyperparameters of the model (e.g., elements of $\boldsymbol{R}$ and $\boldsymbol{Q}$) by maximising the likelihood function.

The TVP-VAR model allows us to extract the time-varying coefficients that quantify each country's dynamic relationships between international trade, uncertainty, and stock market volatility. These coefficients are then analysed using Dynamic Factor Models to identify common factors driving the dynamics across countries. They are then decomposed into trend, seasonal, and cycle components to fully understand the underlying patterns.

3.3 Dynamic Factor Models

After obtaining the time-varying coefficients from the TVP-VAR model for each country, we apply a Dynamic Factor Model (DFM) to identify commonalities in these coefficients across the 15 European countries. The DFM helps to distill the shared underlying dynamics by extracting common factors that drive the evolution of these coefficients.

The DFM with one factor can be specified as follows:

$$X_t = \Lambda F_t + \epsilon_t$$

where:
- X_t is an $n \times 1$ vector of observed time-varying coefficients (for n countries) at time t,
- Λ is an $n \times 1$ vector of factor loadings,
- F_t is a scalar common factor at time t,
- $\epsilon_t \sim \mathcal{N}(0, R)$ is the idiosyncratic error vector.

The common factor F_t captures the shared dynamics across countries, while the factor loadings Λ indicate the extent to which the common factor influences each country's time-varying coefficients.

The DFM can also be represented in state-space form, with the observation specified as:

$$X_t = \Lambda F_t + \epsilon_t$$

where:
- X_t is the $n \times 1$ vector of observed coefficients,
- Λ is the $n \times 1$ vector of factor loadings,
- F_t is the scalar common factor,
- $\epsilon_t \sim \mathcal{N}(0, R)$ is the observation noise.

The state equation is the following:

$$F_t = \phi F_{t-1} + \eta_t$$

where:
- ϕ is the autoregressive coefficient of the factor,
- $\eta_t \sim \mathcal{N}(0, Q)$ is the state noise.

The estimation of the DFM involves the setting of initial values for the common factor F_1 and its covariance matrix, the employment of the Kalman filter to recursively update the common factor F_t and its covariance matrix for each period t and the estimation of the factor loadings Λ, the autoregressive coefficient ϕ, and the elements of R and Q by maximising the likelihood function.

We extract the common factors that capture the shared dynamics across the 15 European countries by applying the DFM to the time-varying coefficients from the TVP-VAR model. These factors are then decomposed into trend, seasonal, and cycle components to provide a comprehensive understanding of the underlying patterns and their implications for international trade, political uncertainty, and stock market volatility.

4. Results and discussion

The TVP-VAR model's application to each country yielded the series of time-varying coefficients presented in the charts below for a sample of countries. Since these coefficients are time-varying, we have a set of coefficients at each moment in time. Therefore, we show tables with descriptive statistics for the values of these coefficients across time in Appendix 1. The charts in Figure 1 illustrate the dynamic coefficients from the TVP-VAR analysis for France, Germany, Romania, and Poland. Each figure presents the time-varying impacts of the first lag of trade, uncertainty, and stock market volatility on the contemporaneous values of these variables. The analysis reveals diverse patterns and interactions among the variables in these four countries.

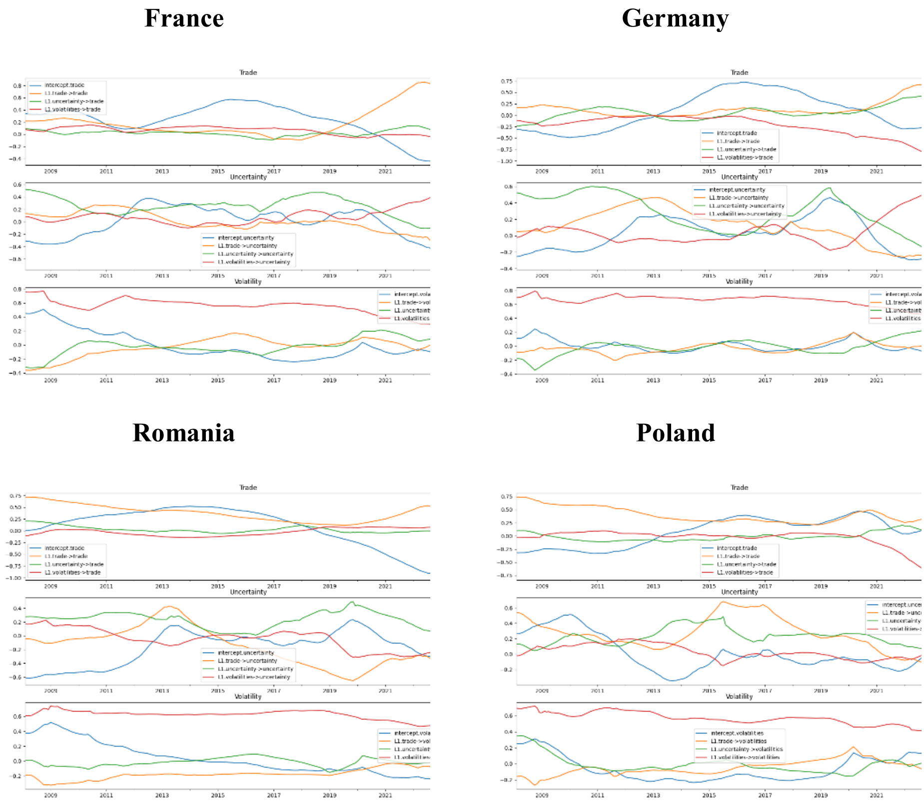


Figure 1. Time-varying coefficients extracted from the TVP-VAR model
Source: Authors' own creation.

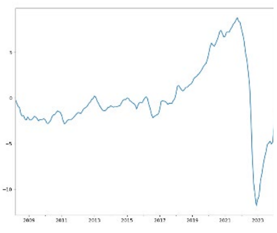
For France, the impact of past trade on current trade shows a stable pattern with minor fluctuations until around 2018, followed by an increase until 2022 and a slight decline afterwards. This suggests a consistent influence of trade activities, with a boost in recent years potentially due to changes in trade policies or external economic shocks. Similar stability is observed in Germany's trade dynamics, reflecting the country's robust and consistent trade activities over the years. Notable fluctuations around 2012 and 2020 in Germany correspond to periods of global economic uncertainty, indicating the responsiveness of trade to broader economic conditions. Romania and Poland also exhibit stable trade dynamics. Romania shows a slight upward trend toward 2022, indicating an increasing influence of past trade on current trade activities. This might reflect Romania's growing integration into European and global trade networks. Poland's trade dynamics reveal minor fluctuations, with a noticeable peak around 2021, suggesting periods of economic growth or policy changes that boosted trade activities.

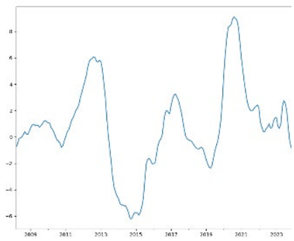
The impact of trade on uncertainty varies significantly across the countries. France shows moderate fluctuations with a peak around 2023, indicating intermittent but significant impacts of trade on uncertainty, especially during heightened economic or geopolitical tensions. Germany exhibits significant variability, with peaks around 2014 and 2018 suggesting substantial impacts of trade-related events and policies on political uncertainty. Romania and Poland also show variability, with notable peaks around 2013 and 2023 for Romania and around 2015 and 2017 for Poland, reflecting the influence of trade events and broader economic conditions on political uncertainty. When examining the influence of political uncertainty on stock market volatility, France displays a relatively low and stable impact of trade on volatility, with more variability observed in the impact of political uncertainty on volatility. This pattern suggests that while trade has a limited direct effect, political uncertainty plays a more pronounced role in influencing market conditions.

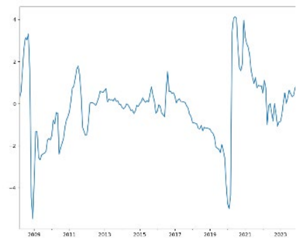
The dynamic coefficients reveal that the relationships between international trade, uncertainty, and stock market volatility are complex and vary across countries. While some consistent patterns are observed, such as the stable influence of trade on trade, significant variability exists in how these variables interact during economic and political changes. These findings highlight the importance of understanding the country-specific dynamics to inform economic policy and market stability strategies. The persistent influence of past volatility on current volatility, particularly noted in Germany and Poland, underscores the self-reinforcing nature of market volatility, emphasising the need for targeted interventions to mitigate its effects.

To analyse the dynamics of the interactions among these three variables, which can generally be noticed across all countries, we used the Dynamic Factor Model with one factor to extract the commonality of these dynamics. Figure 2 shows the evolution of each factor for each DFM applied for each coefficient. The first row of Figure 2 shows the situation for the impact generated by the first lag of international trade. The first chart in this row illustrates the dynamics of the common factor derived from the DFM for the coefficient representing the impact of the first lag of trade on contemporaneous trade across all countries. The trend shows a gradual increase from 2009 to 2022, indicating that the influence of past trade on current trade strengthened during this period, possibly due to increasing economic integration and interdependence among European countries. However, a sharp decline is observed around 2022. The subsequent recovery in 2023 reflects the gradual normalisation of trade flows as economies adjusted to the new realities of the pandemic and resumed international trade activities.

Lag 1 Trade on Trade **Lag 1 Trade on Uncertainty** **Lag 1 Trade on Volatilities**







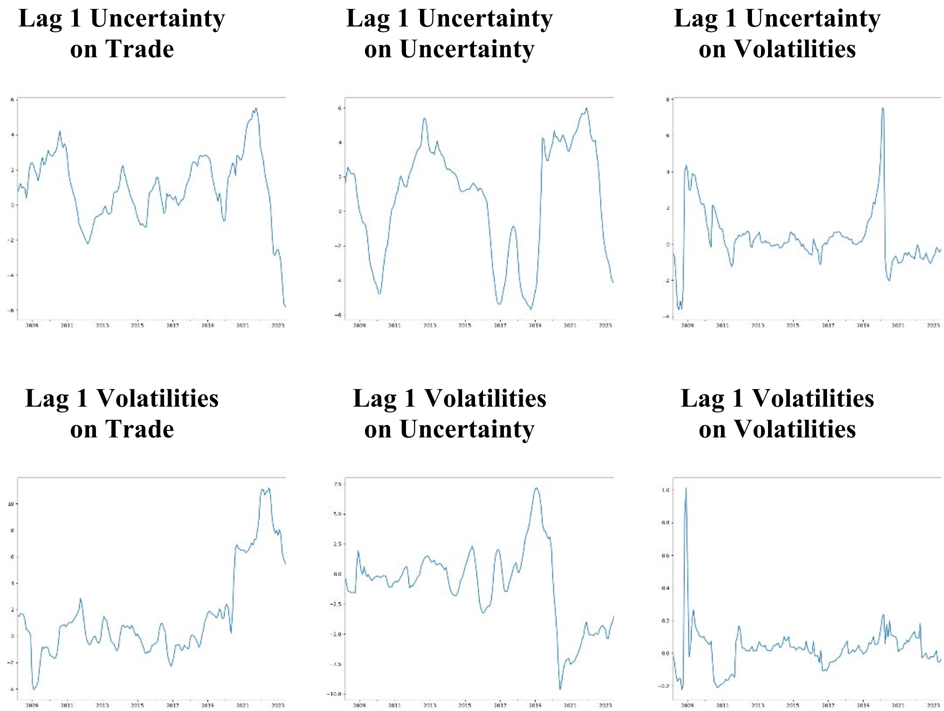


Figure 2. Factors for each coefficient from the DFM
Source: Authors' own creation.

The second chart in the first row depicts the dynamics of the common factor for the coefficient representing the impact of the first lag of trade on political uncertainty. This factor exhibits significant fluctuations, with peaks around 2012, 2017, and 2021, suggesting that past trade activities pronouncedly impacted political uncertainty during these periods. These peaks align with notable economic and geopolitical events, such as the European sovereign debt crisis, Brexit, and the global trade tensions exacerbated by the pandemic. The recurrent peaks indicate that trade disruptions and changes have periodically heightened political uncertainty, underscoring the sensitivity of political stability to trade dynamics. The third chart shows the dynamics of the common factor for the coefficient representing the impact of the first lag of trade on stock market volatility. The factor reveals considerable variability, with notable peaks around 2009, 2012, and 2020. The peak in 2009 corresponds to the aftermath of the global financial crisis, reflecting heightened market volatility driven by trade disruptions. The peaks in 2012 and 2020 align with periods of economic instability and uncertainty, including the European debt crisis and the COVID-19 pandemic. These fluctuations suggest that past trade activities significantly influence market volatility, with heightened trade uncertainty leading to increased market fluctuations. The persistence of these peaks underscores the ongoing relevance of trade dynamics in shaping stock market behaviour and investor sentiment.

The second row of Figure 2 corresponds to the dynamics of the factors resulting from the DFM model, the impact of which is provided by the first lag of policy uncertainty. The first chart illustrates the dynamics of the common factor from the DFM for the coefficient representing the impact of the first lag of political uncertainty on contemporaneous trade across all countries. The trend shows significant fluctuations, with notable peaks around 2010, 2014, and 2018, and a sharp decline in 2020, followed by a rapid recovery in 2021. This pattern suggests that past political uncertainty has had varying, but often substantially impacted, trade activities. The peaks likely correspond to heightened geopolitical tensions and policy uncertainty, such as the European sovereign debt crisis and Brexit, which disrupted trade flows. The sharp decline in 2020 indicates the COVID-19 pandemic's severe impact on global trade, while the subsequent recovery reflects the resilience and adjustment of trade networks as economies adapted to the new normal. The second chart shows the dynamics of the common factor for the coefficient representing the impact of the first lag of political uncertainty on contemporaneous political uncertainty. This factor exhibits pronounced cyclical behaviour with peaks around 2010, 2013, 2016, and 2020. These cycles indicate that political uncertainty tends to propagate over time, with past uncertainty influencing current uncertainty significantly. The recurrent peaks align with major political and economic events that heightened uncertainty, including financial crises, policy changes, and significant elections or referenda. The sharp peaks in 2016 and 2020 highlight the profound impact of events such as Brexit and the COVID-19 pandemic on political stability across Europe. The third chart depicts the dynamics of the common factor for the coefficient representing the impact of the first lag of political uncertainty on stock market volatility. The factor reveals considerable variability, with significant peaks around 2009, 2015, and 2020. The 2009 peak corresponds to the aftermath of the global financial crisis, which caused increased market volatility driven by heightened uncertainty. The peaks in 2015 and 2020 reflect periods of economic instability and uncertainty, including the European debt crisis and the COVID-19 pandemic. These fluctuations suggest that past political uncertainty significantly influences market volatility, with increased uncertainty leading to heightened market fluctuations. The persistent variability underscores the ongoing relevance of political events and policies in shaping market behaviour and investor sentiment.

The final row in Figure 2 illustrates the role of stock market volatility as a driving factor. The first chart highlights the dynamics of the common factor from the DFM, specifically for the coefficient reflecting the influence of lagged stock market volatility on current trade across countries. The trend indicates a marked increase from 2014 to 2020, suggesting an amplified impact of prior market volatility on trade during this period, with notable peaks around 2018 and a sharp rise towards 2020. This trend correlates with heightened market volatility due to geopolitical tensions, economic uncertainty, and the COVID-19 pandemic, significantly affecting trade flows. A subsequent decline beginning in 2022 indicates stabilisation as markets adjusted post-pandemic. The second chart shows the common factor dynamics for the coefficient measuring the impact of lagged stock market volatility on current political uncertainty. This factor reveals significant fluctuations, with peaks in 2013, 2018, and 2020, corresponding to major global and regional events that increased market volatility and political uncertainty, such as the European debt crisis, trade wars, and the pandemic. The decline in 2020 suggests a temporary reduction in uncertainty after the pandemic's initial impact, but the rising trend in 2021-2022 indicates persistent concerns. The third chart presents the dynamics of the common factor for the coefficient representing the impact of lagged stock market volatility on current volatility. Peaks around 2009 and 2020 correspond to the global financial crisis and the COVID-19 pandemic, highlighting periods of extreme market turbulence and the reinforcing nature of volatility during crises. The relative stability from 2011 to 2019 reflects a period of market calm, disrupted by occasional spikes due to events like the European debt crisis. These observations underscore the ongoing sensitivity of markets to volatility shocks and the inherent uncertainties in the global financial landscape.

To gain a comprehensive understanding of the underlying patterns in the time series of dynamic coefficients obtained from the DFM, we decompose each time series into trend, seasonal, and cycle components. This methodological approach isolates long-term movements, regular periodic fluctuations, and irregular cyclical variations within the data. The time series is decomposed using the Seasonal-Trend decomposition using the Loess (STL) method. This technique is chosen for its flexibility and robustness in handling various data types, including those with strong seasonal effects and irregular fluctuations.

The trend component represents the data's long-term progression, capturing the time series' underlying direction. It is extracted by applying a smoothing operation to the original time series, effectively filtering out short-term fluctuations and seasonal variations. Mathematically, the trend component T_t at time t is obtained as follows:

$$T_t = \text{LoessSmoothing}(Y_t)$$

where Y_t is the original time series of dynamic coefficients and LoessSmoothing denotes the locally weighted regression used to smooth the series.

The seasonal component captures regular, repeating patterns within the data that occur at specific intervals (e.g., monthly, quarterly, or annually). These periodic fluctuations are extracted by isolating the intra-year variations from the detrended series. The seasonal component S_t at time t is obtained by:

$$S_t = \frac{1}{N} \sum_{k=1}^{N} (Y_t - T_t)_{(t+k\cdot P)\text{mod}P}$$

where N is the number of periods, P is the periodicity (e.g., 12 for monthly data), and mod denotes the modulo operation to wrap around the periodic index.

The cycle component, or residual component, represents the irregular fluctuations and cyclical variations after removing the trend and seasonal effects. This component captures the short-term and unexpected deviations in the time series. The cycle component C_t at time t is computed as the difference between the original time series and the sum of the trend and seasonal components:

$$C_t = Y_t - T_t - S_t$$

The STL decomposition is applied to each DFM time series of dynamic coefficients. We first apply Loess smoothing to extract the trend component T_t, then we detrend the series by subtracting the trend component and then isolate the seasonal component S_t. In the end we perform residual calculation through which we compute the cycle component C_t by removing both the trend and seasonal components from the original series.

The result of this decomposition is a detailed breakdown of each time series into its fundamental components, enabling us to analyse and interpret the long-term trends, seasonal patterns, and cyclical variations in the dynamic relationships between international trade, political uncertainty, and stock market volatility across the 15 European countries. This decomposition methodology provides valuable insights into the distinct aspects of the dynamic coefficients, highlighting how long-term structural changes, regular seasonal effects, and irregular economic shocks contribute to the series' overall behaviour. By understanding these components, we can better interpret the evolving interdependencies among the key economic variables under study.

This analysis is reflected in Figure 3. The first set of charts (Figure 3, left) represents the decomposition of the factor that captures the impact of lagged international trade on contemporaneous international trade. The trend component shows a relatively stable pattern from 2008 to 2022, with slight fluctuations. A notable decline is observed starting from 2022, reaching a trough around 2023, followed by a slight increase towards 2024. This trend indicates that the influence of past trade on current trade remained stable for a decade but started declining in recent years, possibly due to global trade tensions, protectionist policies, or the impact of the COVID-19 pandemic. The seasonal component exhibits a consistent annual cycle with peaks and troughs, indicating a strong seasonal effect on how past trade impacts current trade. The magnitude of the seasonal fluctuations remains relatively constant over time, suggesting that certain times of the year consistently experience higher or lower impacts due to seasonal factors such as holidays, fiscal year-end activities, or agricultural cycles. The cycle component reveals irregular fluctuations, with notable peaks around 2010, 2015, and a significant spike in 2022, followed by a sharp decline. These cyclical variations could be associated with economic shocks, policy changes, or other irregular events impacting trade dynamics.

The second set of charts (Figure 3, middle) shows the decomposition of the factor capturing the impact of lagged international trade on political uncertainty. The trend component displays a cyclical pattern with three major peaks around 2013, 2017, and 2020, followed by a decline toward 2024. This cyclical trend suggests that the influence of past trade on political uncertainty is not constant and is influenced by broader economic and political cycles, including financial crises and major geopolitical events. The seasonal component demonstrates a pronounced annual cycle, indicating that the impact of past trade on political uncertainty has a significant seasonal element. This pattern may reflect regular political events such as elections, budget cycles, or international trade negotiations at specific times of the year. The cycle component shows considerable irregular fluctuations, with increased volatility around 2010 and 2020. These cycles likely correspond to significant political events or periods of heightened uncertainty, such as financial crises, Brexit, or major policy announcements.

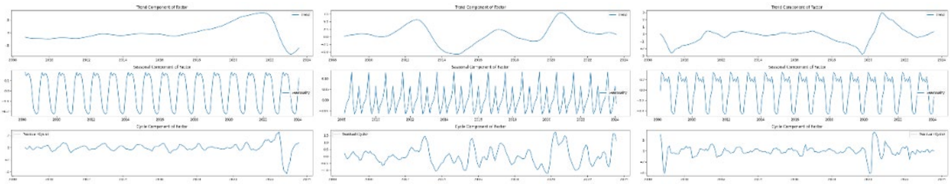


Figure 3. Impact of International Trade on the other variables and itself

Source: Authors' own creation.

Note: left: impact of the lag of international trade on itself; middle: impact of the lag of international trade on political uncertainty; right: impact of the lag of international trade on stock market volatilities.

The third set of charts (Figure 3, right) illustrates the decomposition of the factor capturing the impact of lagged international trade on stock market volatility. The trend component reveals a more volatile long-term pattern with several peaks and troughs. Notable peaks are observed around 2008, 2014, and a significant peak around 2020, followed by a decline towards 2024. This volatility in the trend suggests that the relationship between past trade and stock market volatility is influenced by major economic events and market cycles, such as the global financial crisis, the European debt crisis, and the COVID-19 pandemic. The seasonal component displays a clear and consistent annual pattern, with regular fluctuations that indicate a strong seasonal influence. The consistency of these seasonal patterns suggests that stock market volatility due to past trade is influenced by predictable annual cycles, possibly linked to corporate earnings seasons, fiscal policy announcements, and other regular financial events. The cycle component shows substantial irregular fluctuations, with significant peaks around 2010 and 2020. These cycles reflect periods of heightened market instability and volatility, which may be attributed to unexpected economic shocks, geopolitical tensions, or market corrections.

The uncertainty is depicted in Figure 4. The first set of charts (Figure 4, left) represents the decomposition of the factor capturing the impact of lagged uncertainty on contemporaneous international trade. The trend component shows a relatively stable pattern from 2008 to 2016, with slight fluctuations. A notable decline is observed starting from 2022, reaching a trough around 2023, followed by a slight recovery towards 2024. This trend indicates that the influence of past political uncertainty on current trade remained stable for several years but started to decline in recent years, potentially due to global political events and crises that affected trade stability. The seasonal component exhibits a consistent annual cycle with regular peaks and troughs, indicating a strong seasonal effect on how past political uncertainty impacts current trade. The magnitude of the seasonal fluctuations remains relatively constant over time, suggesting that certain times of the year consistently experience higher or lower impacts due to seasonal factors such as election cycles, policy announcements, and geopolitical events. The cycle component reveals irregular fluctuations, with notable peaks around 2010, 2014, and a significant spike in 2020, followed by a sharp decline. These cyclical variations could be associated with economic shocks, sudden political changes, or other irregular events impacting trade dynamics.

The second set of charts (Figure 4, middle) shows the decomposition of the factor capturing the impact of lagged political uncertainty on contemporaneous political uncertainty. The trend component displays a cyclical pattern with three major peaks around 2008, 2012, and 2016, followed by a decline toward 2024. This cyclical trend suggests that the influence of past political uncertainty on current political uncertainty is not constant and is influenced by broader political and economic cycles, including periods of significant geopolitical tensions and policy changes. The seasonal component demonstrates a pronounced annual cycle, indicating that the impact of past political uncertainty on current political uncertainty has a significant seasonal element. This pattern may reflect regular political events, such as elections, budget cycles, or international summits, that occur at specific times of the year. The cycle component shows considerable irregular fluctuations, with increased volatility around 2010 and 2020. These cycles likely correspond to significant political events or periods of heightened uncertainty, such as financial crises, geopolitical conflicts, or major policy announcements.

The last set of charts (Figure 4, right) illustrates the decomposition of the factor capturing the impact of lagged political uncertainty on stock market volatility. The trend component reveals a volatile long-term pattern with several peaks and troughs. Notable peaks are observed around 2009, 2015, and a significant peak around 2020, followed by a decline towards 2024. This volatility in the trend suggests that the relationship between past political uncertainty and stock market volatility is influenced by major economic events and market cycles, such as the global financial crisis, the European debt crisis, and the COVID-19 pandemic. The seasonal component displays a clear and consistent annual pattern, with regular fluctuations that indicate a strong seasonal influence. The consistency of these seasonal patterns suggests that stock market volatility due to past political uncertainty is influenced by predictable annual cycles, possibly linked to fiscal policy announcements, corporate earnings seasons, and other regular financial events. The cycle component shows substantial irregular fluctuations, with significant peaks around 2010 and 2020. These cycles reflect periods of heightened market instability and volatility, which may be attributed to unexpected economic shocks, geopolitical tensions, or market corrections.

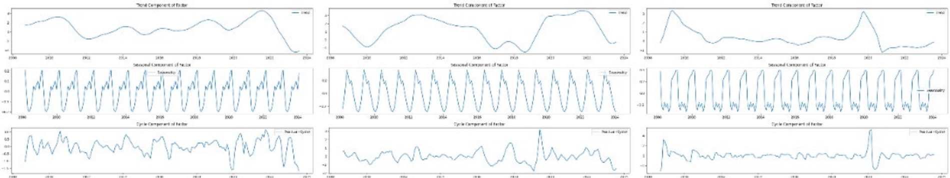


Figure 4. Impact of political uncertainty on the other variables and itself
Source: Authors' own creation.
Note: left: impact of the lag of political uncertainty on international trade on itself; middle: impact of the lag of political uncertainty on itself; right: impact of the lag of political uncertainty on stock market volatilities.

Figure 5 shows the results for volatility. On the left side of Figure 5 we can see the decomposition of the factor capturing the impact of lagged stock market volatility on contemporaneous international trade. The trend component shows a relatively stable pattern from 2008 to 2016, with slight fluctuations. A significant increase is observed starting from 2016, peaking around 2022, followed by a decline towards 2024. This trend suggests that the influence of past market volatility on current trade remained stable for several years, but began to increase markedly in recent years, likely due to heightened market instability and global economic uncertainties such as the trade wars and the COVID-19 pandemic. The seasonal component exhibits a consistent annual cycle with regular peaks and troughs, indicating a strong seasonal effect on how past market volatility impacts current trade. The magnitude of the seasonal fluctuations remains relatively constant over time, suggesting that certain times of the year consistently experience higher or lower impacts due to seasonal factors such as fiscal year-end activities, quarterly financial reporting, and holiday seasons. The cycle component reveals irregular fluctuations, with notable peaks around 2010, 2014, and a significant spike in 2020, followed by a sharp decline. These cyclical variations could be associated with economic shocks, market corrections, and other irregular events impacting trade dynamics.

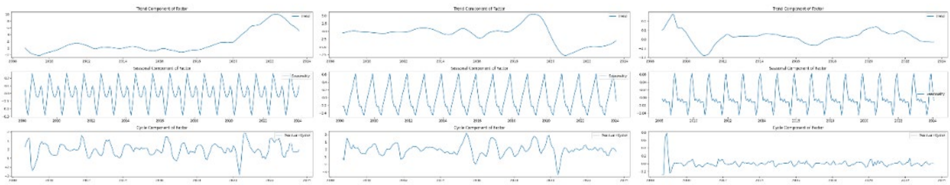


Figure 5. Impact of stock market volatilities on the other variables and itself
Source: Authors' own creation.
Note: left: impact of the lag of stock market volatilities on international trade on itself; middle: impact of the lag of stock market volatilities on itself; right: impact of the lag of stock market volatilities on stock market volatilities.

The charts in the middle of Figure 5 show the decomposition of the factor capturing the impact of lagged stock market volatility on contemporaneous political uncertainty. The trend component displays a relatively flat pattern from 2008 to 2016, with minor fluctuations. A significant decline is observed starting from 2016, reaching a trough around 2020, followed by a slight recovery toward 2024. This trend suggests that the influence of past market volatility on current political uncertainty was minimal and stable for several years, but began to decline in recent years, possibly due to a shift in the sources of political uncertainty or changes in market dynamics. The seasonal component demonstrates a pronounced annual cycle, indicating that the impact of past market volatility on current political uncertainty has a significant seasonal element. This pattern may reflect regular political events, such as elections, budget cycles, and international policy negotiations, at specific times of the year. The cycle component shows considerable irregular fluctuations, with increased volatility around 2010 and 2020. These cycles likely correspond to significant political events or periods of heightened uncertainty, such as financial crises, geopolitical tensions, or major policy announcements.

The last set of charts on the right side of Figure 5 illustrates the decomposition of the factor capturing the impact of lagged stock market volatility on contemporaneous stock market volatility. The trend component reveals a volatile long-term pattern with several peaks and troughs. Notable peaks are observed around 2008, 2014, and a significant peak around 2020, followed by a decline towards 2024. This volatility in the trend suggests that the relationship between past and current market volatility is influenced by major economic events and market cycles, such as the global financial crisis, the European debt crisis, and the COVID-19 pandemic. The seasonal component displays a clear and consistent annual pattern, with regular fluctuations that indicate a strong seasonal influence. The consistency of these seasonal patterns suggests that stock market volatility due to past volatility is influenced by predictable annual cycles, possibly linked to fiscal policy announcements, corporate earnings seasons, and other regular financial events. The cycle component shows substantial irregular fluctuations, with significant peaks around 2010 and 2020. These cycles reflect periods of heightened market instability and volatility, which may be attributed to unexpected economic shocks, geopolitical tensions, or market corrections.

5. Concluding Remarks

This paper investigated the dynamic interdependencies between international trade, uncertainty, and stock market volatility across 15 European countries. We employed a TVP-VAR model on the monthly data and applied a DFM on the extracted dynamic coefficients. We aimed to identify common factors driving these evolutions. Each factor was further decomposed into trend, seasonal, and cycle components to provide a comprehensive understanding of the underlying patterns.

We were able to detect significant variability in these relationships in different countries and periods. Major economic events such as the European sovereign debt crisis, Brexit, and the COVID-19 pandemic are moments when these dynamics showed interesting patterns. The decomposition analysis highlighted the persistent influence of trade and volatility on uncertainty, with notable peaks during periods of important economic and geopolitical tensions. Stock market volatility also exhibited self-reinforcing behaviour, especially during financial crises, while the seasonal components had regular periodic influences. These results have several implications. Understanding the dynamic interdependencies can aid in designing more effective economic policies that stabilise trade flows and market conditions considering also that the unique economic realities of each country make it challenging to apply uniform measures effectively (Haller et al., 2020). Additionally, insights into how trade and uncertainty influence market volatility set the stage for better risk management and investment strategies. Moreover, businesses engaged in international trade can use the methodology developed here to create strategies that mitigate the risks associated with general political and economic uncertainty and stock market volatility.

An extension of this work could delve into the investigation of the impact of other macroeconomic variables, such as interest rates and inflation, on the dynamics of trade, uncertainty, and stock market volatility. Applying similar methodologies to other regions or emerging markets could also provide a broader perspective on the global interconnectedness of these economic variables, while further refinement of the models, including higher-order lags and the incorporation of structural breaks, could enhance the robustness and accuracy of the findings.

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Appendix 1 – Descriptive statistics for time-varying coefficients of TVP-VAR

	lag 1 trade on trade					lag 1 trade on uncertainty					lag 1 trade on volatilities				
	min	**25%**	**50%**	**75%**	**max**	**min**	**25%**	**50%**	**75%**	**max**	**min**	**25%**	**50%**	**75%**	**max**
Austria	-1.095	-0.644	-0.24	-0.078	2.699	-1.354	-0.779	-0.34	0.989	2.319	-1.83	-0.449	-0.143	0.288	2.944
Belgium	-1.799	-0.796	0.197	0.919	1.66	-1.993	-0.98	0.423	0.788	1.405	-3.18	-0.066	0.195	0.306	2.533
Czech Republic	-1.492	-0.841	-0.303	1.054	1.749	-1.838	-0.62	-0.219	0.206	2.386	-2.766	-0.708	0.147	0.654	2.401
Germany	-1.02	-0.629	-0.314	0.154	2.685	-1.666	-0.534	-0.021	0.633	1.761	-2.479	-0.694	-0.059	0.403	3.191
Spain	-1.307	-0.912	-0.286	0.684	1.923	-3.07	-0.62	0.47	0.74	1.036	-2.263	-0.458	0.092	0.777	1.944
France	-1.219	-0.697	-0.294	0.182	2.488	-2.037	-0.55	-0.104	0.683	1.962	-2.641	-0.372	0.163	0.728	1.481
United Kingdom	-1.677	-0.681	0.121	0.416	2.942	-1.522	-0.977	0.262	0.645	1.972	-1.998	-0.761	-0.183	0.554	2.722
Greece	-1.211	-0.817	-0.445	1.047	2.003	-2.277	-0.505	-0.138	0.671	2.738	-1.506	-0.755	-0.216	0.446	2.565
Hungary	-1.27	-0.75	-0.244	0.522	2.923	-2.811	-0.458	0.144	0.725	2.068	-1.643	-0.771	-0.126	0.231	3.207
Ireland	-2.884	-0.517	0.168	0.619	1.54	-2.186	-0.644	0.249	0.85	1.291	-2.551	-0.573	-0.133	0.47	2.506
Italy	-1.343	-0.916	-0.238	0.819	2.121	-1.675	-0.66	-0.03	0.981	1.572	-2.93	-0.58	0.107	0.582	2.394
Netherlands	-1.772	-0.905	0.342	0.592	1.906	-1.532	-0.766	0.072	0.584	2.261	-1.561	-0.608	-0.148	0.524	3.575
Poland	-1.307	-0.795	-0.385	0.741	2.431	-1.712	-0.659	-0.057	0.608	1.983	-2.545	-0.62	-0.008	0.508	3.012
Romania	-1.532	-0.859	0.078	0.638	2.069	-1.901	-0.709	0.045	0.532	2.232	-2.023	-0.308	-0.198	0.583	2.077
Sweden	-1.384	-0.761	-0.231	0.436	2.484	-2.686	-0.391	0.297	0.683	1.393	-1.573	-0.493	-0.239	0.418	3.038

	lag 1 uncertainty on trade					lag 1 uncertainty on uncertainty					lag 1 uncertainty on volatilities				
	min	**25%**	**50%**	**75%**	**max**	**min**	**25%**	**50%**	**75%**	**max**	**min**	**25%**	**50%**	**75%**	**max**
Austria	-1.793	-0.729	-0.262	0.884	1.893	-1.51	-0.892	-0.046	0.806	1.63	-3.195	-0.335	0.224	0.521	2.184
Belgium	-1.284	-0.793	-0.338	0.658	2.229	-2.474	-0.554	0.048	0.859	1.597	-2.825	-0.427	0.052	0.612	2.001
Czech Republic	-1.546	-0.763	-0.209	0.42	2.919	-1.618	-0.678	0.029	0.632	1.91	-1.906	-0.393	-0.131	0.201	3.288
Germany	-1.939	-0.605	-0.184	0.463	2.103	-1.749	-0.908	-0.033	0.938	1.502	-2.759	-0.597	0.003	0.541	1.896
Spain	-1.872	-0.588	0.095	0.797	1.916	-1.652	-0.881	-0.015	0.85	1.881	-1.119	-0.743	-0.453	0.661	2.732
France	-2.381	-0.521	-0.058	0.489	2.443	-2.21	-0.661	0.129	0.68	1.836	-2.64	-0.537	-0.026	0.681	1.865
United Kingdom	-2.783	-0.524	0.144	0.656	2.214	-0.979	-0.74	-0.415	0.5	2.901	-2.931	-0.298	0.009	0.667	2.425
Greece	-1.64	-0.42	-0.175	0.264	2.588	-1.508	-0.945	-0.075	0.481	1.849	-1.226	-1.03	-0.031	0.954	1.972
Hungary	-1.741	-0.626	-0.01	0.373	2.63	-1.465	-0.778	-0.437	1.011	1.736	-2.045	-0.772	0.265	0.811	1.524
Ireland	-1.62	-0.746	-0.032	0.819	2.137	-2.79	-0.215	0.11	0.508	2.298	-2.456	-0.696	-0.035	0.671	2.051
Italy	-1.259	-0.83	-0.283	0.816	1.943	-1.988	-0.82	-0.005	0.819	1.644	-2.751	-0.61	0.055	0.985	1.638
Netherlands	-1.602	-0.719	-0.177	0.48	2.564	-2.176	-0.198	0.164	0.629	1.887	-4.008	-0.368	0.177	0.665	1.263
Poland	-1.258	-0.864	-0.199	0.885	2.298	-1.596	-0.865	-0.029	0.403	2.5	-1.452	-0.615	-0.197	0.314	3.531
Romania	-1.292	-0.741	-0.28	0.428	2.806	-1.865	-0.845	0.226	0.744	2.346	-2.511	-0.685	-0.031	0.627	2.049
Sweden	-1.481	-1.102	0.011	0.934	1.656	-1.662	-1.05	0.151	0.992	1.397	-2.049	-0.725	0.228	0.701	1.608

	lag 1 volatilities on trade					lag 1 volatilities on uncertainty					lag 1 volatilities on volatilities				
	min	25%	50%	75%	max	min	25%	50%	75%	max	min	25%	50%	75%	max
Austria	-3.267	-0.046	0.305	0.594	0.915	-1.358	-0.742	-0.105	0.309	2.383	-2.091	-0.341	0.132	0.762	2.087
Belgium	-2.562	-0.42	-0.117	0.863	1.382	-1.566	-0.568	-0.308	0.636	2.112	-1.86	-1.023	0.28	0.544	3.614
Czech Republic	-1.809	-1.041	0.389	0.716	1.562	-1.995	-0.549	0.213	0.866	1.261	-1.915	-0.476	-0.003	0.66	2.714
Germany	-2.623	-0.59	0.359	0.81	0.962	-1.31	-0.672	-0.334	0.133	2.484	-2.175	-0.318	0.405	0.664	1.694
Spain	-2.672	-0.632	0.43	0.623	1.361	-1.661	-0.665	-0.38	0.875	1.826	-2.032	-0.745	0.433	0.738	1.291
France	-2.319	-0.811	0.324	0.832	1.452	-1.308	-0.674	-0.307	0.266	2.803	-1.961	-0.348	0.201	0.601	1.949
United Kingdom	-2.158	-0.798	0.548	0.687	1.468	-2.011	-0.992	0.433	0.821	1.341	-2.128	-0.039	0.261	0.749	2.008
Greece	-2.126	-0.828	0.145	0.893	1.522	-1.573	-0.989	-0.103	0.713	2.364	-3.445	-0.161	0.073	0.665	1.558
Hungary	-3.246	-0.481	0.236	0.757	1.303	-2.139	-0.478	0.077	0.583	1.657	-1.875	-0.69	0.024	0.366	3.009
Ireland	-3.113	-0.322	0.257	0.802	1.046	-2.111	-0.387	-0.066	0.034	3.055	-1.282	-0.829	0.019	0.404	3.836
Italy	-2.822	-0.16	0.23	0.732	1.017	-1.894	-0.788	0.053	0.768	2.039	-1.925	-0.628	0.158	0.783	1.804
Netherlands	-2.119	-0.767	0.215	0.747	1.646	-2.355	-0.66	0.134	0.571	2.501	-2.009	-0.613	0.008	0.766	2.772
Poland	-2.85	0.207	0.381	0.555	0.761	-2.022	-0.792	-0.206	0.923	1.79	-2.275	-0.612	0.103	0.784	1.755
Romania	-1.607	-0.963	0.144	1.034	1.417	-1.713	-0.756	0.176	0.669	1.903	-2.271	-0.604	0.225	0.718	1.91
Sweden	-2.756	-0.091	0.319	0.677	1.018	-1.594	-0.901	-0.464	0.693	1.844	-1.514	-0.637	-0.11	0.459	3.978