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# Time-Varying Spillover of US Trade War on the Growth of Emerging Economies

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**Time-Varying Spillover of US Trade War on the Growth of Emerging Economies**

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**Abstract**

In the wake of an unprecedented increase in the trade policy-related uncertainty of the US since 2017, we analyze the ability of a newspaper-based trade policy uncertainty index of the US in predicting the growth rate of emerging market economies using a novel multivariate time-varying causality framework. We provide overwhelming evidence of the role of trade uncertainty in negatively impacting the growth of emerging markets in a statistically significant manner, with the effect being on the rise since the Great Recession. Our results are robust to the usage of an alternative econometric methodology, metric of trade uncertainty, and also over an out-of-sample forecasting exercise. Policy conclusions of our results are discussed.

**Keywords:** Trade Policy Uncertainty of the United States, Time-Varying Multivariate Causality, Emerging Market Economies
**JEL Codes:** C32, E32

## 1. Introduction

The role of economic uncertainty in causing the "Great Recession" in the United States (US) has been studied widely, as has been the influence of the same on other advanced and emerging economies (see, Gupta et al., (2018, 2019) for detailed literature reviews in this regard). In terms of the spillover of US uncertainty on other economies (via financial, exchange rate, trade channels), studies have shown that the contraction of emerging markets is equal if not more for emerging markets when compared to the US and other advanced countries (Carrière-Swallow and Céspedes, 2013; Gupta et al., forthcoming). Given that, uncertainty in the US economy has primarily been driven by trade policy related uncertainty, since the start of the administration of President Donald J. Trump in 2017 (Ahir et al., 2019), recent studies have directed their attention to highlighting the negative impact of trade uncertainty on the (firm- and aggregate-levels of) investment and output of the US economy (Caldara et al., 2019a), as well as that of investment in Europe (Ebeke and Siminitz, 2018).

Against this backdrop, given the importance of emerging markets in the global economy through their trade linkages (Ruzima and Boachie, 2018), to the extent that the BRICS (Brazil, Russia, China, India, South Africa) are forecasted to to surpass the G7 countries by 2050 in terms of contribution to global output (Plakandaras et al., 2019), and the fact that the heightened trade uncertainty has primarily resulted from the recent US-China trade war, our paper analyzes for the first time the predictive ability of trade policy related uncertainty of the US on growth rate of output of emerging economies,

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controlling for the same for the US and other advanced countries.[1] In our econometric analysis, we use a time-varying approach, in particular, the recently proposed multivariate time-varying causality framework of Rossi and Wang (forthcoming), which in turn help us to analyze the evolution of the predictability of trade uncertainty on the outgrowth of emerging markets over the quarterly period of our analysis, i.e., 1984:Q3 to 2019:Q3. The time-varying method is crucial in our case, given that trade uncertainty has spiked-up only recently (as is depicted in Figure A1 in the Appendix of the paper) following a prolonged period of calm. The remainder of the paper is organized as follows: Section 2 presents the data and the methodology, while Section 3 discusses the results, with Section 4 concluding the paper.

## 2. Data and Methodology

Our analysis involves four variables, the real Gross Domestic Product (GDP) of the US, other advanced and emerging market economies, with the latter two treated as economic blocs, and a metric for trade-related policy uncertainty. The real GDP data is obtained from the Global Economic Database maintained by the Federal Reserve Bank of Dallas, which is available for download from: https://www.dallasfed.org/institute/dgei/gdp.aspx.[2] Uncertainty is a latent variable, and hence is not straightforward to measure, given this we use the trade policy uncertainty (TPU) index of the US as developed by Caldara et al., (2019a). The index is constructed by counting the frequency of joint occurrences of trade policy (tariff, import duty, import barrier, and anti-dumping) and uncertainty (uncertainty, risk, or potential) terms across major newspapers (Boston Globe, Chicago Tribune, Guardian, Los Angeles Times, New York Times, Wall Street Journal, and Washington Post). The data is downloadable from the website of Professor Matteo Iacoviello at: https://www2.bc.edu/matteo-iacoviello/tpu.htm. Based on data availability, our analysis covers the quarterly period of 1984:Q2 to 2019:Q3, and the variables have been plotted in Figure A1 in the Appendix of the paper. As can be seen in general, the TPU is quite constant with mild increases around the North American Free Trade Agreement (NAFTA) negotiations in the mid-1990s. However, the TPU reaches unprecedented levels beginning after the 2016 US Presidential Election and spikes several times in response to heightened tensions between the US and its trading partners, particularly China and Mexico.[3]

Because of the simplicity of the classical linear Granger causal test, it is one of the most commonly used methods for testing in-sample predictability. However, Vector Autoregressive (VAR) model-based analyses face major technical difficulties in macro-economic data since economic time series are generally vulnerable to instabilities, thereby resulting estimates of VARs are also sensitive to instabilities (Boivin and Giannoni, 2006; Clark and McCracken, 2006; Rossi, 2013). Moreover, the traditional Granger-causality test requires stationarity, which in turn may lead to an erroneous inference in the presence of instabilities. In order to overcome these limitations, Rossi and Wang (forthcoming) propose a robust causality test, which is more powerful than the traditional Granger-causality test,

[1] The only other paper to have looked into this issue is that by Caldara et al., (2019b), who indicate that that trade uncertainty of the US negatively impacts the growth rate of industrial production in emerging economies. But, these authors use a constant parameter model, and hence cannot provide a time-varying analysis.

[2] The reader is referred to Grossman et al., (2014) for further details. Data on 18 advanced (excluding the US, Japan, Germany, the United Kingdom (UK), France, Italy, Spain, Canada, South Korea, Australia, Taiwan, The Netherlands, Belgium, Sweden, Austria, Switzerland, Greece, Portugal, and Czech Republic, in order of Purchasing Power Parity (PPP)-adjusted GDP shares in 2005) and 21 emerging (China, India, Russia, Brazil, Mexico, Turkey, Indonesia, Poland, Thailand, Argentina, South Africa, Colombia, Malaysia, Venezuela, Philippines, Nigeria, Chile, Peru, Hungary, Bulgaria, and Costa Rica, in order of PPP-adjusted GDP shares in 2005) countries are used to compile the aggregates for these blocs, by using trade weights with the US in weighting the country-level data.

[3] For a detailed up-to-date guide of the US trade-wars, the reader is referred to the timeline at: https://www.piie.com/blogs/trade-investment-policy-watch/trump-trade-war-china-date-guide.

following the time-varying methodologies suggested by Rossi (2005). Moreover, in our particular case, with TPU becoming more prominent recently, the approach helps us to analyze the time-varying impact on the growth rate of the emerging countries, and hence, provide a more appropriate inference of the effect rather than a constant parameter Granger causality method.

In this study, we consider the following VAR model with time-varying parameters:

$$y_t = \Psi_{1,t} y_{t-1} + \Psi_{2,t} y_{t-2} + \cdots + \Psi_{p,t} y_{t-p} + \varepsilon_t \tag{1}$$

where $\Psi_{j,t}$ , $j = 1, \ldots p$ are functions of time varying coefficient matrices, $y_t = [y_{1,t}, y_{2,t}, \ldots, y_{n,t}]'$ is an $(nx1)$ vector and the idiosyncratic shocks $\varepsilon_t$ are assumed to be heteroscedastic and serially correlated.

The variables included in our VAR constitutes of the three endogenous variables namely, GDP growth rates of the US, other advanced economies and emerging market economies, besides the TPU index. We test the null hypothesis that TPU does not Granger cause emerging market growth rate for all *t* where the null hypothesis is $H_0$: $\phi_t = 0$ for all $t = 1,2, \ldots, T$, given that $\phi_t$ is appropriate subset of $vec\ (\Psi_{1,t}, \Psi_{2,t}, \ldots, \Psi_{p,t})$. To this end, Rossi (2005) suggested four alternative test statistics namely: the exponential Wald (*ExpW*), mean Wald (*MeanW*), Nyblom (*Nybolm*) and Quandt Likelihood Ratio (*SupLR*) tests. Based on the Akaike Information Criterion (AIC), the VAR model is estimated with 2 lags. The econometric approach used in our paper requires the usage of stationary data, and hence the three GDPs with unit roots, are converted into their growth rates, but since the TPU is stationary in levels,[4] we work with its natural logarithms, giving us an effective sample period of 1984:Q3 to 2019Q3, i.e., 141 observations. In an effort to cover as much of data, we use an end-point trimming of 10% rather than the usual 15% used in the structural break literature, which in turn amounts us to losing 14 observations from both ends.

## 3. Empirical Analyses

### 3.1. Main Results

In Table 1, to analyze the predictive ability of TPU for the growth rate of emerging market GDP, we first started with the standard constant parameter Granger causality test and found no evidence of TPU to Granger cause the growth rate of the emerging countries. In contrast, when we look at the *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests of Rossi and Wang (forthcoming) based on the time-varying VAR also reported in Table 1, the null of no-Granger causality from TPU to the growth of GDP for the emerging markets are overwhelmingly rejected at the highest possible level of significance across all the four tests. In other words, the predictive ability of TPU for the growth rate of the emerging countries are time-varying.[5]

**[INSERT TABLE 1]**

Next, in Figure 1, we present the whole sequence of the Wald statistics across time, which gives more information on when the Granger-causality occurs. As can be seen, TPU consistently predicts the growth of emerging market economies, with the effect increasing after the Great Recession.

[4] Complete details of the unit root tests are available upon request from the authors.
[5] This result is not surprising, since based on the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), used to detect 1 to *M* structural breaks in the equation for the growth rate of emerging markets of the VAR(2) model, allowing for heterogenous error distributions across the breaks and 10% trimming, yielded 5 break points at: 1990:Q4, 1995:Q1, 1998:Q2, 2002:Q3, 2009:Q2.

**[INSERT FIGURE 1]**

As indicated above, since trimming leads to a loss of about 14 observations from both ends of the sample period, we revisit our results by taking two alternative routes to minimize the loss of observations especially towards the end of our sample period when trade uncertainty increased tremendously. In the first case, we re-conduct the Rossi and Wang (forthcoming) test by using a VAR(1) model as suggested by the Schwarz Information Criterion (SIC), which in turn also allows us to use a trimming of only 5% due to the usage of one lag.[6] As can be seen from Figure 2, when we lose about 7 observations from both ends, the results are similar to those reported in Figure 1, but the longer coverage of data shows a sudden jump in the time-varying Wald statistics suggesting a sharp increase in predictability post-2015, and reaching a peak at around mid-2016. Though the effect falls thereafter, it still remains at higher levels observed before the Great Recession.

**[INSERT FIGURE 2]**

In the second case, we use the bootstrapped recursive, rolling, and recursive-rolling multivariate tests of Shi et al., (2018, forthcoming) to check for time-varying causality from TPU to the growth of the emerging economies using a VAR(2) model. Based on an initial window of 0.20 of the total sample, i.e., 28 quarters and 500 bootstrap replications recommended by the original papers, results are reported in Figure 3 for recursive, rolling and recursive-rolling approaches. As can be seen from the figure, we find evidence of causality consistently over the sample period, primarily under the rolling and recursive-rolling approaches, with peaks around the beginning of the sample period (corresponding to NAFTA negotiations), and during the Great Recession, and smaller peaks consistently during the recent trade war. Though, not as strong as under the full-fledged time-varying approach during the administration of President Trump, the predictability of emerging market growth rate due to TPU is undeniable.

**[INSERT FIGURE 3]**

While the time-varying predictive analysis is the focus of our paper, causality tests are silent about the sign of the impact of TPU on the GDP growth of the emerging markets. Given this, as a final part of the main analysis, we estimate a time-varying parameter VAR model with stochastic volatility (TVP-VAR-SV) as developed by Primiceri (2005), and Del Negro and Primiceri (2015) with 2 lags, and analyze the time-varying impact on the GDP growth rate of the emerging economies following a shock to the TPU index. The TPU shock is identified using a standard Cholesky identification scheme, whereby the TPU index is followed by the growth rates of the US, other advanced economies and that of the emerging markets.

The TVP-VAR model is estimated using Markov-Chain Monte-Carlo (MCMC) methods with Bayesian inference, based on 70,000 draws after an initial burn-in of 30,000 (i.e., we use a total of 100,000 iterations). The MCMC method assesses the joint posterior distributions of the parameters of interest based on certain prior probability densities that we set in advance, which in turn, are identical to those used in Primiceri (2005), Del Negro and Primiceri (2015). Once the model is estimated, we can produce time-varying impulse response functions of the variables in the model following the one standard deviation of the TPU shock. Below, in Figure 4, we present the time-varying response of the GDP growth rate of the emerging markets over a horizon of six years. In essence, the impact is sharp and

[6] Again, as under the AIC, using a VAR(1), while the standard Granger causality test could not reject the null hypothesis even at the 10% level of significance, the four time-varying tests overwhelmingly rejected, at the highest level of significance, the hypothesis of no Granger causality test from TPU to the growth rate of emerging markets. Complete details of these results are available upon request from the authors.

negative on the impact of the TPU shock throughout the sample period of 1984:Q3 to 2019:Q3, with the strongest impact felt during the Great Recession.[7] Interestingly, while the effect of post-2016 is relatively small, it is clearly quite persistent.

**[INSERT FIGURE 4]**

In sum, TPU has time-varying predictive content, particularly post the Great Recession, for the growth rate of emerging economies, with the effect being negative over the entire sample period.

### 3.2. Robustness Analyses

As part of our robustness analysis, we conduct the Rossi and Wang (forthcoming) test of time-varying predictability test, over 1984:Q3 to 2018:Q4 (based on data availability), using an alternative measure of trade policy uncertainty developed by Caldara et al., (2019a), which is estimated using a stochastic volatility model for import tariff rates.[8] Again, we conduct the analysis under AIC-based VAR(3) and SIC-based VAR(1) models with trimming of 10% and 5% respectively, now using the natural logarithms of tariff volatility besides the 3 growth rates of GDP.[9] As can be seen from Figure 5 under the VAR(3) model, tariff volatility consistently predicts the growth rate of emerging economies, with the effect peaking-up from 2010. A similar pattern is observed in Figure 6 for the VAR(1) model, though evidence of predictability is not consistent over the entire sample period. But in essence, trade uncertainty derived from tariff volatility, as under the news-based metric of trade policy-related uncertainty, has predictive content for the GDP growth of emerging countries.

**[INSERT FIGURES 5 AND 6]**

Since the in-sample predictability of the TPU index, does not guarantee out-of-sample forecastability, in addition, we estimated various (Bayesian) constant and time-varying parameters VAR and VAR Moving Average (VARMA) models, with and without stochastic volatility as proposed by Chan and Eisenstat (2017). As reported in Table 2, based on an initial in-sample period of 1984:Q3-2000:Q4, the relative (to the random walk model) log predictive likelihoods at horizons of 1-, 2-, and 3-quarter-ahead confirms the ability of the TPU to forecast the density of the growth of the GDP of emerging economies over a recursively-estimated out-of-sample period (2001:Q1-2019:Q3),[10] with highest gains observed under the constant and time-varying VARMA models with stochastic volatility.

**[INSERT TABLE 2]**

In other words, the TPU can predict GDP growth of emerging markets both in- and out-of-sample.

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[7] We also observed negative time-varying impacts on the growth rate of the US and other advanced economies following the TPU shock, with time-varying impulse responses from the TVP-VAR model available upon request from the authors.

[8] Note that Baker et al. (2016) also construct a TPU index using newspaper searches. However, since we use the tariff volatility as the measure of trade-related uncertainty for robustness purposes, we decided to rely on the TPU index developed by Caldara et al., (2019a) as part of our main analysis for the sake of consistency. The tariff volatility data, like the TPU index, is again downloadable from the website of Professor Matteo Iacoviello.

[9] Again, the four time-varying tests overwhelmingly rejected, at the highest level of significance, the hypothesis of no Granger causality test from tariff volatility to the growth rate of emerging markets. Complete details of these results are available upon request from the authors.

[10] The in- and out-of-sample splits ensure that the latter covers the two latest deepest recessions of the US, i.e., the early 2000s recession and the Great Recession, as well as the hike in the TPU since 2017.

## 4. Conclusion

There has been an unprecedented increase in the trade policy-related uncertainty of the US since 2017 due to multiple trade-wars coinciding with President Trump taking office. In this paper, we analyze the ability of a recently developed newspaper-based trade policy uncertainty index of the US in predicting the future path of the growth rate of emerging market economies using a novel multivariate time-varying causality framework, which controls for the impact on the output growth of the US and other advanced countries. We provide overwhelming evidence of the role of trade uncertainty in predicting the growth of emerging markets in a statistically significant manner, with the effect being on the rise since the Great Recession. Our results are robust to the usage of an alternative econometric methodology, metric of trade uncertainty related to tariff volatility, and also over an out-of-sample forecasting exercise. Moreover, a time-varying impulse response analysis shows that a shock to trade uncertainty reduces the growth rate of the emerging markets. Our results imply that policymakers in emerging countries must be aware of the possible threat of an upcoming recession in the wake of heightened trade policy uncertainty in the US, and hence, must be ready to undertake necessary (expansionary) policies to prevent a downturn in their respective domestic economies.

While we analyze the impact of trade policy uncertainty of the US on the aggregate emerging economies bloc, as part of future analysis, it would be interesting to delve into individual major emerging.

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**Table 1.** Constant parameter and time-varying parameter Granger causality tests

| | $\chi^2(2)$ | *ExpW* | *MeanW* | *Nyblom* | *SupLR* |
|---|---|---|---|---|---|
| Test Statistic | 2.9279 | 444.2838 | 300.2182 | 694.3689 | 897.9860 |
| *p*-value | 0.2313 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

**Note:** Null hypothesis is the TPU does not Granger cause growth of GDP of emerging economies in a constant or time-varying VAR(2), which includes growth of GDP of the US and other advanced economies as additional variables.

**Table 2.** Relative log predictive likelihoods for 1, 2-, and 3-quarter-ahead density forecasts (compared to the random walk model)

| | Forecast Horizon | | |
|---|---|---|---|
| Models | 1-quarter-ahead | 2-quarter-ahead | 3-quarter-ahead |
| VAR(2) | 7.5 | 20.4 | 28.4 |
| VAR(2)-SV | 15.1 | 32.0 | 38.9 |
| VARMA(2,1) | 5.9 | 19.6 | 27.5 |
| VARMA(2,1)-SV1 | 19.3 | 33.5 | 39.3 |
| VARMA(2,1)-SV2 | 21.1 | 34.0 | 39.9 |
| TVP-VARMA(2,1)-SV2 | 19.3 | 30.3 | 36.0 |

**Note:** The order of the VAR is 2, while that of the MA component is 1; SV stands for stochastic volatility, with SV1 and SV2 corresponding to models of stochastic volatility without and with the time-varying MA part.

**Figure 1.** Time-varying Wald statistics with VAR(2) under AIC, testing whether TPU Granger-causes the GDP growth rate of emerging economies

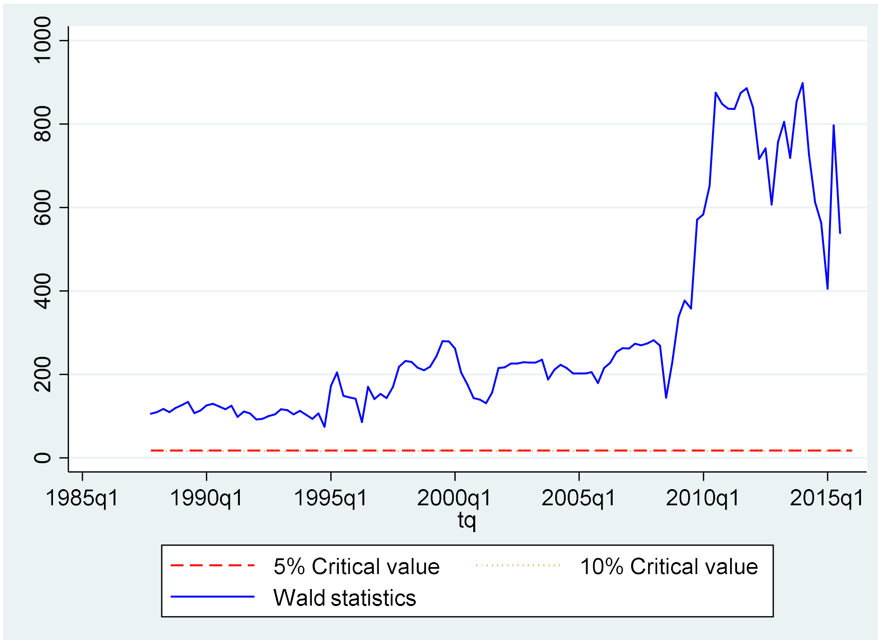



**Figure 2.** Time-varying Wald statistics with VAR(1) under SIC, testing whether TPU Granger-causes the GDP growth rate of emerging economies

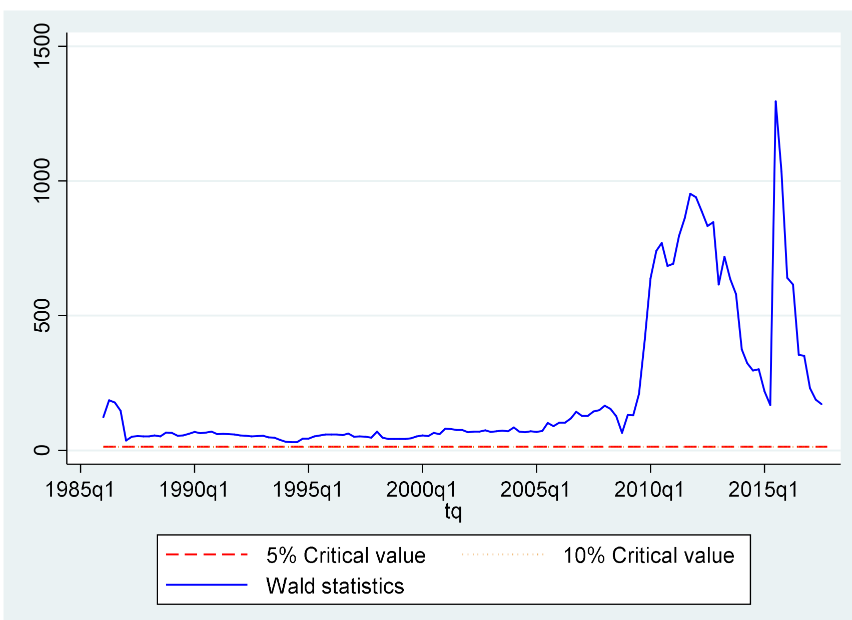
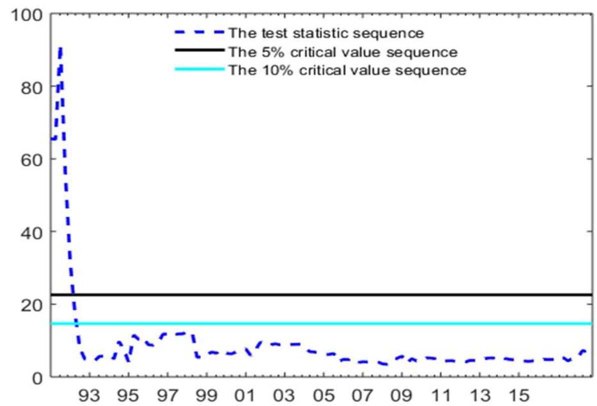
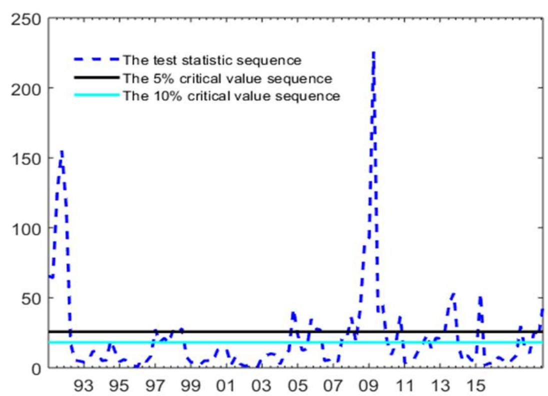


**Figure 3:** Results for recursive, rolling and recursive-rolling methods, testing whether TPU Granger-causes the GDP growth rate of emerging economies

(a) Recursive




(b) Rolling




(c) Recursive-Rolling

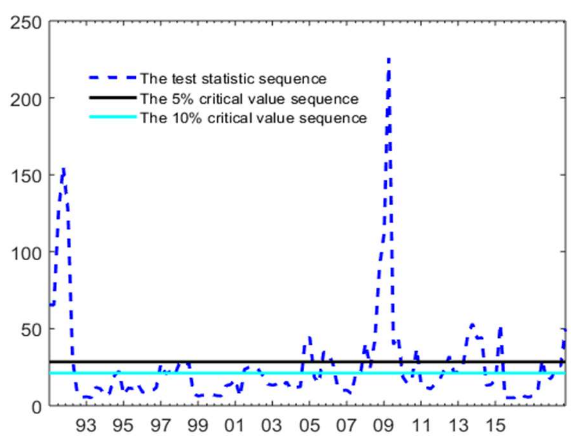


**Figure 4.** Response of GDP growth rate of emerging economies to a one standard deviation TPU shock in the TVP-VAR model

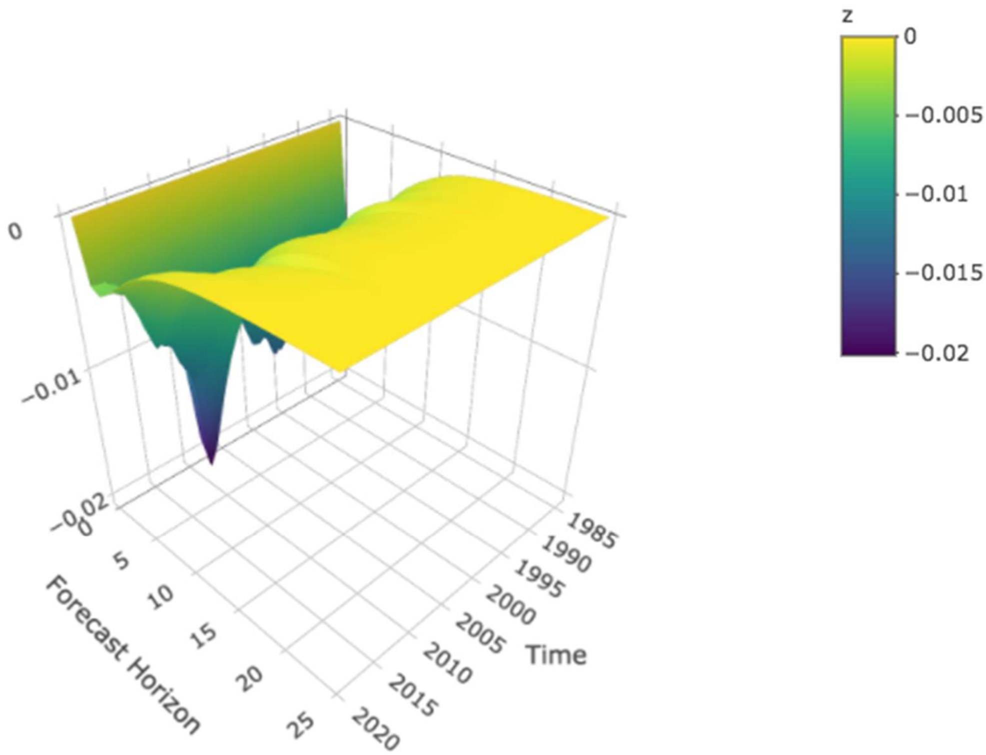


**Figure 5.** Time-varying Wald statistics with VAR(3) under AIC, testing whether tariff volatility Granger-causes the GDP growth rate of emerging economies

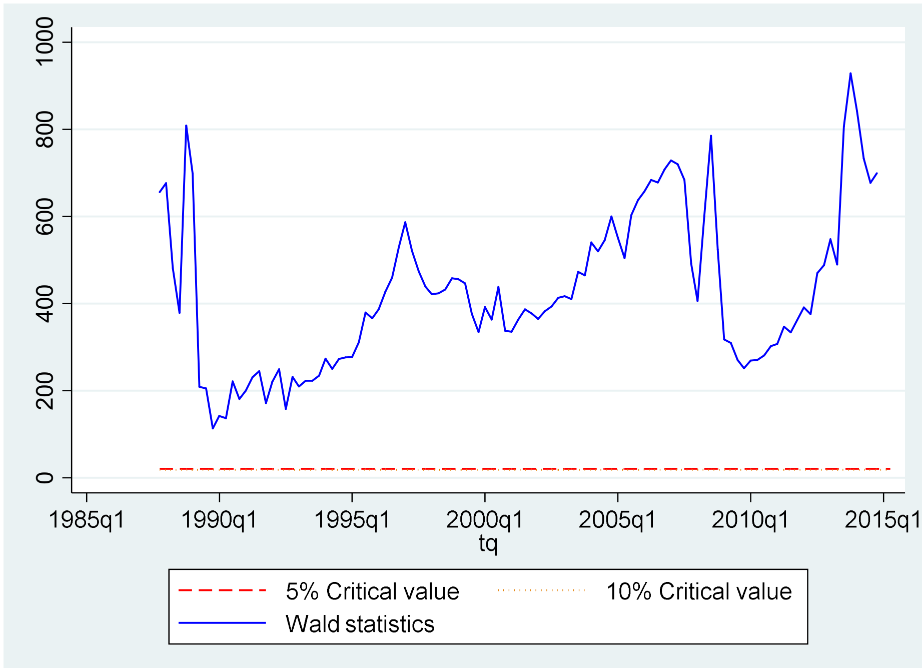
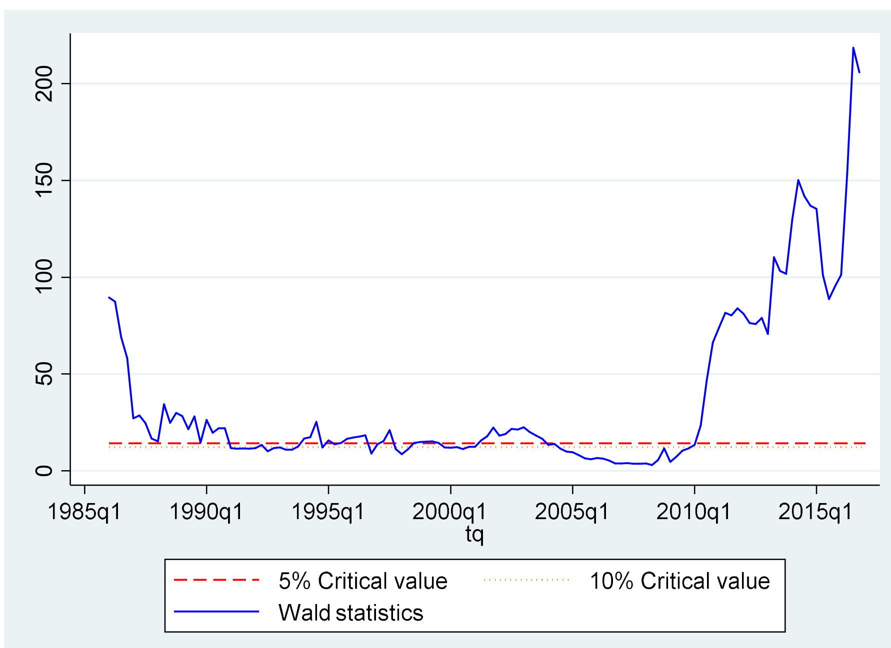



**Figure 6.** Time-varying Wald statistics with VAR(1) under SIC, testing whether tariff volatility Granger-causes the GDP growth rate of emerging economies



**APPENDIX:**

**Figure A1.** Data Plots