The impact of trade policy uncertainty shocks on the Euro Area

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Abstract

This paper sets up a Bayesian SVAR model on Euro Area data and identifies trade policy uncertainty shocks using a minimum set of sign restrictions. We find that rising trade policy uncertainty adversely affects the real business cycle in the Euro Area mostly in short term, while it has more persistent effects on the Euro effective exchange rate and, to a lesser extent, on prices. In line with the recent geo-political events, the evidence suggests an increasing contribution to Euro Area fluctuations towards the end of the sample period. The results are robust to alternative measures of trade policy uncertainty. Furthermore, we show that sectors exhibit heterogeneous responses to trade policy uncertainty shocks.

Keywords: Trade policy uncertainty; Euro Area; uncertainty shocks; Bayesian SVAR; sign restrictions.

JEL Classification: C32, D80, E30, F13.

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*The views presented herein are those of the authors and do not necessarily represent the official views of Bank of Slovenia or of the Eurosystem.

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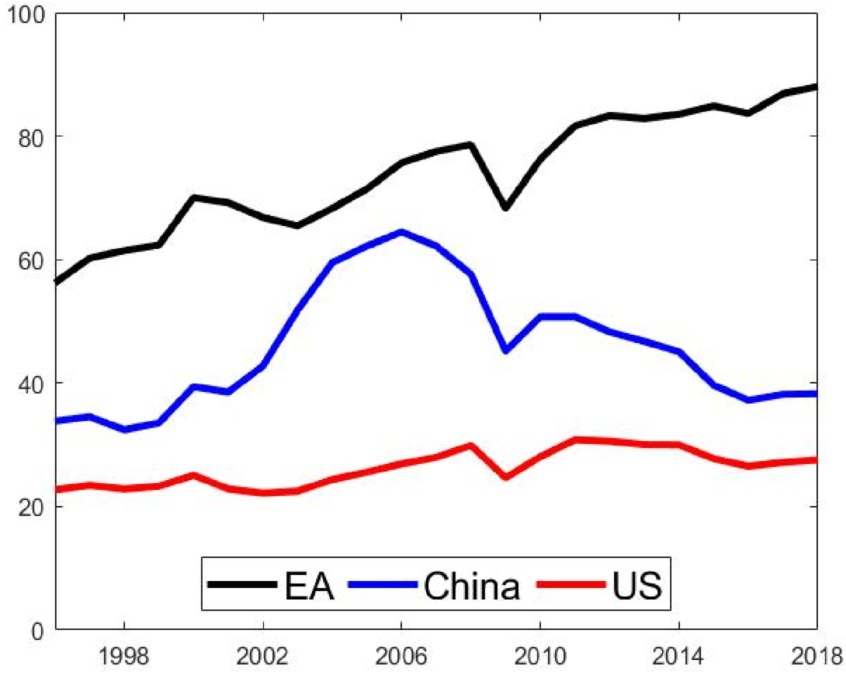
1 Introduction

Many developments in the global geo-political environment have prompted a renewed discussion on the role of policy uncertainty on particular economies. We can regard the Brexit vote, the height of the sovereign debt crisis in Europe, the economic policy uncertainties, and after all the outbreak of the US-China trade war starting in 2018 as one of the main factors that have shaped economic activities over the last couple of years. Indeed, these events had paved the way for the tightening of trade conditions severely, which have curbed economic exchanges at global level. The first main contribution related to quantifying the economic relevance of such an environment is provided by Caldara *et al.* (2020). In their application on the US economy, they study the effects of trade policy uncertainty (henceforth, TPU), highlighting the magnitude of real impacts and stressing evidence of contraction for business investment.

In this paper, we analyze the reaction of the Euro Area (henceforth, EA) business cycle to TPU shocks. To this aim, we estimate a number of structural shocks identified with a minimum set of sign restrictions in a Bayesian SVAR model setting. We rely on Furlanetto *et al.* (2019) when deciding to use the sign restriction methodology to identify uncertainty shocks. The choice to identify several shocks relies on two important aspects. First, it allows to disentangle the source of fluctuations driving the state of the economy in the region considered, over the sample period. Second and more importantly, it reduces the issue that arises from sign restrictions, i.e. the so-called "multiple shocks problem" (Fry and Pagan, 2011; Furlanetto *et al.*, 2019). As in Furlanetto *et al.* (2019), sign restrictions are used to identify, among the other shocks, uncertianty shocsl.

The exact purpose of the paper is to understand the effects that TPU may have on economically relevant actors, like the EA. The employment of the EA as our study case for this application is motivated by various reasons. First, as suggested by Figure 1, the EA openness (sum of exports and imports as percent of GDP) has substantially increased over the last 15 years, reinforcing the dependence of the EA to global market events. Second, the proportion of EA trade activities with the US and China has also risen significantly over the last decade, strengthening the weight of the two trading partners for the domestic economy and boosting the possibility of cross-country economic spillovers. Furthermore, the Brexit situation will soon represent another non-negligible source of fluctuations for EA trade-related activities and it will gain greater relevance in the very near future, especially at the point of policy decisions.

Figure 1: Openness of the EA, US and Chinese economies - sum of exports and imports as percent of GDP (yearly data)

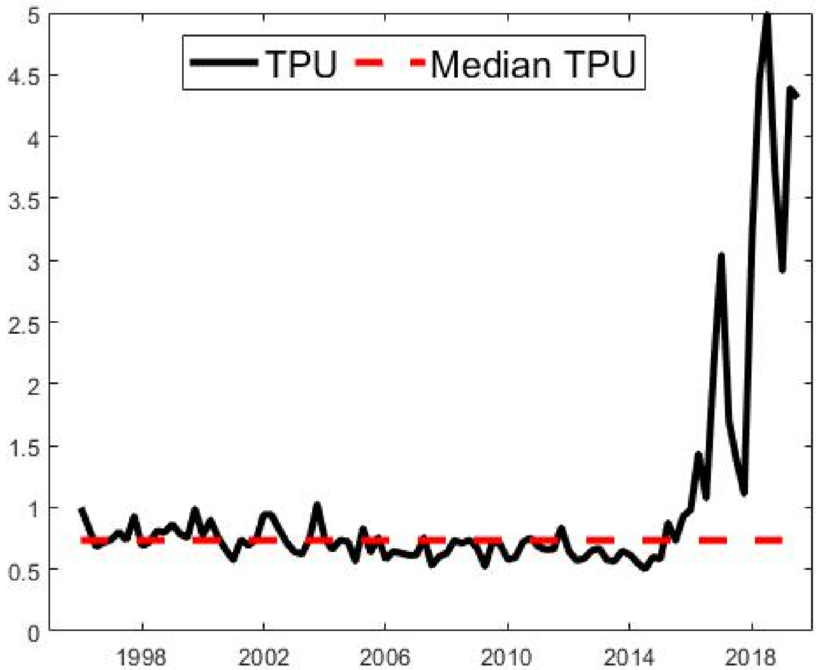


Source: World Bank.

The measurement of trade policy uncertainty is performed by including the news-based index of aggregate TPU developed by Caldara *et al.* (2020). To build the index, Caldara *et al.* (2020) collected articles about topics related to TPU from the seven main US newspapers and quantitatively aggregate them according to some factors which are reported in detail in their paper. The TPU index is plotted in Figure 2 and it covers the period between 1996:Q1 and 2019:Q3. It can easily be seen that along its dynamics, periods of upswings of uncertainty in trade policies are present. This is particularly evident in the recent years with the onset of the US-China trade war, as the index has risen way above its historical median.[1] The analysis of the Euro Area is complemented with the identification of other shocks, either nominal or real, either domestic or global.

The empirical results suggest the following main findings. First, we find that TPU shocks have significant effects on the EA and especially on prices and mostly on the Euro effective exchange rate (henceforth, Euro EER). Second, replacing the TPU index with a different measure of TPU confirms the robustness of our baseline evidence. Moreover, we show that TPU shocks have a non-homogeneous magnitude on the real activities, according to the sector that we consider.

Figure 2: Trade policy uncertainty index



Source: Caldara et al. (2020)

With regard to the existing literature, several authors have already studied the economic effects of different types of policy uncertainties. Put broadly, there are two

[1]We depict the median of the TPU index since the latest (trade policy) developments significantly affect the mean values of the index.

strands of literature. On the empirical side, the focus of the literature is mainly related to the measurement of the policy uncertainties. Fernández-Villaverde *et al.* (2015), for instance, study the effects of changes in uncertainty about future fiscal policy (fiscal volatility shocks) on aggregate economic activity in the US. In order to construct an indicator of fiscal volatility, they apply a law motion equation for fiscal policy instruments that feed into a New Keynesian business cycle model calibrated to the US economy. Baker *et al.* (2016), on the other hand, develop an index of economic policy uncertainty (EPU index) that is based on newspaper coverage frequency. Similarly, Rice (2020) constructs an Irish version of the EPU index. Hassan *et al.* (2019) analyze the quarterly earnings conference-call transcripts to construct firm-level measures of the extent and type of political risk faced by firms listed in the US and how it varies over time. Caldara *et al.* (2020) focus their research on constructing a trade policy uncertainty indicator (TPU index) that uses newspaper coverage, firms' earning calls and tariff rates setting a study case for the US economy.

The theoretical strand of the literature focuses on the construction and use of several types of theoretical models. Jaimovich and Rebelo (2009) propose a one-sector model that is able to produce aggregate and sectoral co-movement in responses to contemporaneous and news shocks about fundamentals by introducing a capital utilization variable, the investment adjustment costs and a weak wealth effect on the labour supply and at the same time overcoming the criticism of Barro and King (1984). Building upon the theoretical work of Bloom (2009), Basu and Bundick (2017) and Fernández-Villaverde *et al.* (2015) study the macroeconomic effects of uncertainty shocks in a New Keynesian business cycle model setting. Colombo (2013) uses a SVAR model setting in order to estimate the effects of a US economic policy uncertainty shock on EA macroeconomic aggregates. Caggiano *et al.* (2017, 2020) estimate US economic policy uncertainty shocks by using a nonlinear VAR approach. They confirm asymmetric spillover effects, especially that the macroeconomic aggregates react more strongly to uncertainty shocks in the periods of economic busts. They complement the results shown in Caggiano *et al.* (2014) and Nodari (2014).

Based on the recent global trade developments, there is a growing literature explicitly studying the effects of trade policy uncertainty and news about the trade policy, especially between the US and Chinese economies. Handley (2014) provides evidence that the impact of trade policy uncertainty has on exporters based on a dynamic heterogeneous firms model. Handley and Limão (2017) and Crowley *et al.* (2018) papers study the impact of trade policy on China's export boom to the US following its 2001 World Trade Organisation (WTO) accession. Steinberg (2019), on the other hand, estimates the effects of Brexit for the UK economy. Ebeke and Siminitz (2018) focus their analysis on the effects of the trade policy uncertainty on investment in the EA. They assume that economies that are more dependent on global trade networks show a higher investment sensitivity with regards to the trade policy uncertainty.
The rest of the paper is organized as follows. Section 2 presents the theory and the methodology of the Bayesian VAR model. Section 3 discusses the results of the estimation of the baseline model and provides an alternative view of the model. Section 4 concludes.

2 Methodology

2.1 Model

This subsection provides the econometric methodology of a Bayesian SVAR model. In general, Bayesian VAR models impose prior restrictions over the parameters' distribution of a VAR model. The model parameters are obtained by combining the prior distribution with information obtained from the data. Bayesian VAR models became increasingly popular since VAR models can usually suffer from a short data sample problem, thus having low degrees of freedom space. In contrast to VAR models, the Bayesian VAR model methodology enables us to include a larger number of explanatory variables in the time-series analysis. The possible limitation of the number of time observations of separate variables in the model affects only the setting up the tightness of the priors used in the Bayesian VAR methodology. As mentioned before, Bayesian methods were popularized in recent years reflecting the progress made in the econometric and computational tools. The usage of prior information provides a consistent way for forecasting exercises, despite that the choice of prior information could be subjective.

We follow the Furlanetto *et al.* (2019) Bayesian SVAR model setting. The reduced form VAR model is then given by

$$\mathbf{y}_t = \mathbf{c} + \sum_{i=1}^{P} \mathbf{B}_i \mathbf{y}_{t-i} + \mathbf{u}_t \tag{1}$$

where the term $\mathbf{y}_t$ represent a $(N \times 1)$ vector of N endogenous variables. The term $\mathbf{c}$ is a $(N \times 1)$ vector of constants. The terms $\mathbf{B}_i$ are $(N \times N)$ parameter matrices, where $i =, ..., P$ and P represents the number of lags in the model. The vector $\mathbf{u}_t$ is the $(N \times 1)$ reduced form residual where $\mathbf{u}_t \sim N(0, \Sigma)$. Σ is the variance-covariance matrix. Bayesian methods are used for the estimation of the above model, while the variables enter the model in levels. As in Furlanetto *et al.* (2019), we specify diffuse priors so that the information in the likelihood is dominant. These priors lead to a Normal-Wishart posterior with a mean and variance parameters corresponding to the OLS estimates. Additional details are reported in the Appendix.[2]

2.2 Sign restrictions

An important part of the paper is the identification procedure. We can write the prediction error, denoted as $\mathbf{u}_t$, as a linear combination of structural innovations ϵ_t

[2]The Bayesian methodology is based on the likelihood function that follows a Gaussian distribution regardless of the presence of non-stationarity. Therefore, it does not need to take special account of non-stationarity (Sims, Stock, and Watson, 1990; Sims and Uhlig, 1991).

$$\mathbf{u}_t = \mathbf{A}\epsilon_t \tag{2}$$

where for $\epsilon_t \sim N(0, \mathbf{I})$ holds and where the term $\mathbf{I}$ represents an $(N \times N)$ identity matrix. The term $\mathbf{A}$ is a non-singular parameter matrix, so that for variance-covariance matrix the following structure applies, $\Sigma = \mathbf{AA}'$. As the variance covariance matrix is symmetric, $N(N-1)/2$ further restrictions are needed to derive $\mathbf{A}$ from this relationship (Furlanetto *et al.*, 2019).

There are several ways to impose restrictions on the parameter matrix $\mathbf{A}$. In the identification procedure of the Cholesky decomposition, for instance, we restrict the parameter matrix $\mathbf{A}$ to be lower triangular, which implies a recursive identification scheme. In our case, the recursive identification scheme is not particularly theoretically convenient since the model estimation includes some of the fast-moving variables, such are the overnight interbank interest rate (Eonia index) and the Euro EER.[3] This leads us to use an alternative identification procedure that is based on sign restrictions (Faust, 1998; Canova and De Nicoló, 2002; Peersman, 2005; Uhlig, 2005; Fry and Pagan, 2011) which is however used by Furlanetto *et al.* (2019) to identify financial and uncertainty shocks.

The use of the identification procedure with sign restrictions is particularly helpful when we deal with a larger number of shocks despite the fact that there are challenges from a computational perspective. As already anticipated, the identification selection of different shocks is based on two important aspects. First, it allows to obtain a clear picture of the main occurrences impacting the EA. Second, it reduces the issue that can arise from the sign restrictions approach, i.e. the so-called "multiple shocks problem", which arises when sign restriction methodology is applied (see Fry and Pagan, 2011 and Furlanetto *et al.*, 2019). This relates to the fact that the sign restrictions

[3]Similarly as in Rigobon and Sack (2003) and Bjørnland and Leitemo (2010).

imposed are potentially consistent with more than one shock. The "multiple shocks problem" is especially relevant when only one shock is identified. On the other hand, it is arguably less serious in a model with several identified shocks (Furlanetto *et al.*, 2019).

Table 1 presents the restrictions used in the baseline model. It is worth saying that restrictions are imposed only on impact (Canova and Paustian, 2011). Following Peersman (2005) and Peersman and Straub (2006), among others, we assign similar sign restrictions to the demand, supply and monetary policy shocks (Table 1). To deal with potential issues of endogeneity, we assume that demand, supply and monetary policy shocks do not have a preferable sign restriction on the TPU index. In more detail, a positive demand shock increases the output, prices and Euro EER. The interest rates consequently respond with an increase as well. On the other hand, trade balance is affected negatively as the positive demand shock increases the need for economy's imports while rising prices and Euro EER make domestic economy exports less attractive abroad. We also do not assign a sign restriction for TPU index when a demand shock hits the economy. A positive supply shock increases output, but, due to product abundance, decreases prices. Consequently, the Euro EER and interest rate have room to decrease. For the effect of the supply shock on the trade balance we assume that there are no restrictions as import and export dynamics might cancel each other out. As typically in the economic theory, a positive (restrictive) monetary policy shock decreases output, trade balance and prices, while the interest rate and Euro EER increase. Foreign shocks (commodity shocks and foreign demand shocks) are also identified to cover additional and non-negligible dynamics which virtually impact the EA business cycle.

Sign restrictions for the identification of the TPU shock have to be well thought out. In contrast to most of the uncertainty literature, our paper focuses on a narrower definition of uncertainty, *i.e.* the trade policy uncertainty, which is more specific to international trade and economic activity. This allow us to take advantage of dissecting the effects of trade policy uncertainties on economic activity of a particular economy in comparison to a reliance on a more general measure of uncertainty carrying various dimensions that are difficult to interpret. In this perspective, we partly follow the considerations made by Nodari (2014) and Baker *et al.* (2016) with respect to the effects of the financial regulation policy uncertainty (FRPU) index on the macroeconomic variables. An increase in the FRPU index decreases the industrial production and prices. Fed responds by decreasing the key rate. On the other hand, the unemployment rate and bond spreads increase. However, in order to disentangle the shocks between demand and trade policy we consider additional variables in the model such as trade balance and TPU index nevertheless. A positive TPU shock thus negatively affects GDP and prices (see Table 1). Consequently, the monetary policy reacts with a decrease in the key interest rates. The Euro EER decreases as well. On the contrast to the case with the demand shock the trade balance variable in the case of a TPU shock depends both on exports and imports, as they may cancel each other out if GDP and Euro EER decrease (or increase) at the same time.

Table 1: Sign restrictions in the model

Variable	Trade uncert.	Demand	Supply	Monetary policy	Commodity	Global demand
TPU	+	NA	NA	NA	NA	NA
GDP	−	+	+	−	−	+
Prices	−	+	−	−	−	NA
Interest rate	−	+	−	+	−	NA
Euro EER	−	+	−	+	+	+
Trade balance	NA	−	NA	−	−	+

*Note: The restrictions used for each variable (in rows) to the identified shocks (in columns).

2.3 Data

Before we move to the results of the model, lets shortly present the descriptive statistics of the macroeconomic variables entering the model (Table 2). The number of observations of the variables deviates between 92 and 95 due to different lengths of the quarterly time series. The observations of all time series start from 1996:Q1, while the last observation for all the variables is 2019:Q3, except for the tariff volatility index that is only available until 2018:Q4. The TPU and the tariff volatility indices are taken from Caldara *et al.* (2020) paper. The EA GDP indicator is given as the chain linked volumes index based on 2015 constant prices and is expressed in trillions of Euro. Similarly to the EA GDP, the EA trade balance indicator variable is also expressed in trillions of Euro. The nominal variables are the EA HICP index with a base year of 2015, the Eonia index and the Euro EER index. The Eonia index is the Euro overnight index average interest rate of the EA interbank market. It serves a proxy for the key monetary policy rate. The nominal Euro EER index is given as the weighted average of the Euro against a basket of 19 foreign currencies and it can be viewed as an overall measure of the EA's external competitiveness. We also consider a manufacturing indicator data series, that is used for robustness check of the baseline model. Manufacturing is given as the gross value added expressed in trillion of Euro.

Table 2: Descriptive statistics of the variables entering the model

Variable	Number of observ.	Mean	Standard dev.	Minimum	Maximum
TPU index	95	0.43	0.38	0.21	2.07
GDP	95	2.42	0.25	1.90	2.84
HICP	95	0.89	0.11	0.71	1.05
Interest rate	95	1.77	1.68	-0.40	4.83
Euro EER	95	0.99	0.06	0.85	1.13
Trade balance	95	0.06	0.04	0.01	0.14
Tariff volatility index	92	0.09	0.06	0.03	0.45
Manufacturing sector	95	0.36	0.04	0.29	0.44

Source: Eurostat, ECB, Caldara et al. (2020), own calculations.

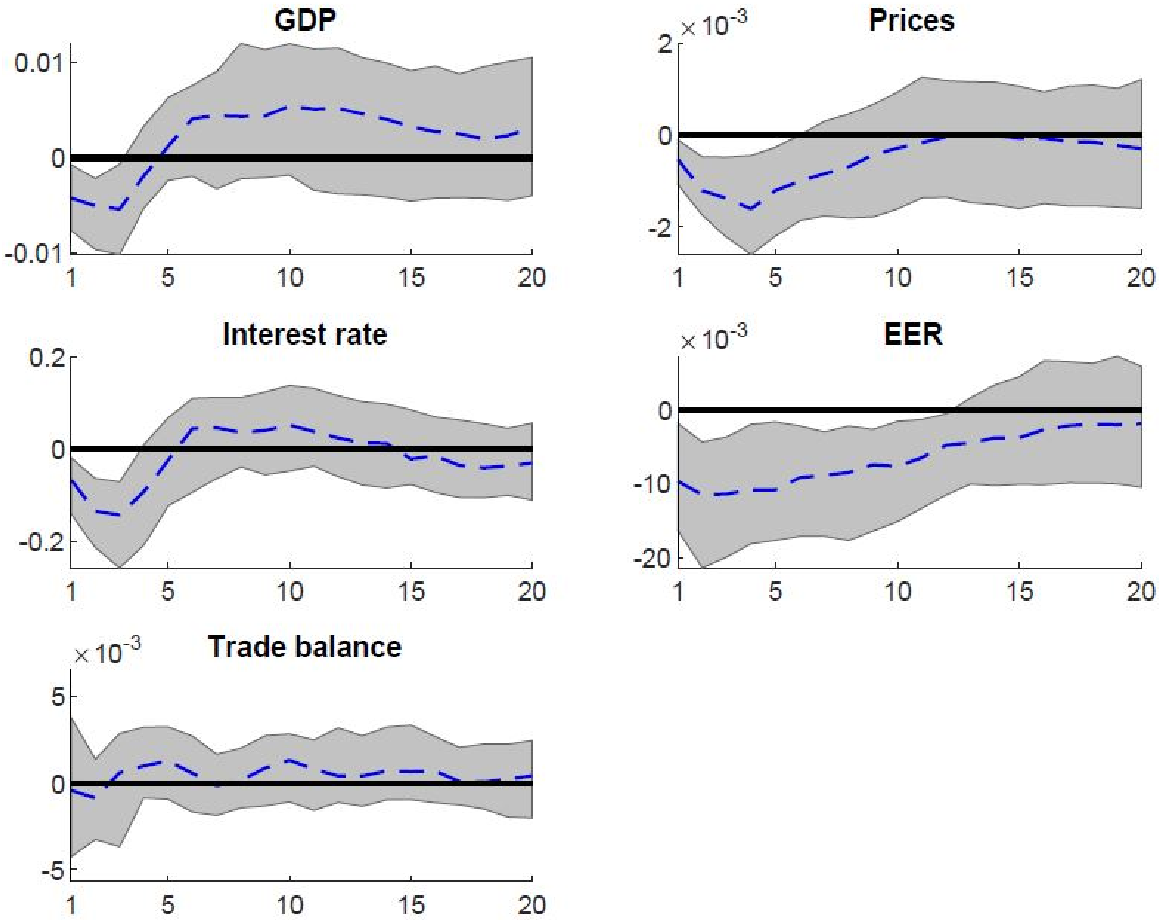
3 Results

This section is dedicated to the presentation of the results that are derived from the estimation of the model. We start with the outcomes related to the baseline model. The baseline VAR model includes 4 lags, which, according to LM test for autocorrelation, are enough to deal with the issue of residual serial correlation. We highlight the empirical evidence through impulse response functions, forecast error variance decomposition and historical decomposition. After that, we move to show the additional outcomes obtained from different specifications.

3.1 Baseline model

Impulse response functions. The baseline model is a six variable Bayesian SVAR model taking into account the TPU index, chain linked GDP index, HICP price index, Euro EER index, trade balance and the Eonia index. In Figure 2 we report the median impulse response functions, together with the 68% credible interval, of the main EA macroeconomic variables to a TPU shock. The results offer several interesting conclusions worth to be mentioned. Most of the EA macroeconomic variables show a significant response to an induced TPU shock. The magnitude of the responses, however, is not homogeneous and differs across the EA macroeconomic variables. Indeed, we can easily note that the significant TPU shock responses of the GDP and the interest rate (Eonia index) last for about 2 to 3 quarters. After that, both variables quickly converge back to the steady state. The effects of the TPU shock on the Euro EER and, to a lesser extent, on HICP prices, on the other hand, are more persistent but smaller in magnitude. Especially, the TPU shocks seem to have a lasting effect on the Euro EER as they generate Euro EER deviations from the steady steady that last more than three years. The trade balance is expectedly not affected by TPU shocks, emphasizing the fact that international competitiveness gained from the exchange rate depreciation is driven by a weak foreign demand and reduced export market (Handley and Limão, 2017). Consequently, this offsets any benefit deriving from cheaper domestic goods. Given these facts, it is worth mentioning the fact that the TPU shocks have a bigger effect on nominal indicators in comparison to the real ones. Referring to the Caldara *et al.* (2020) paper that finds the effects of increased trade policy uncertainty on investment and economic activity in US, we show that the increased trade policy uncertainty also deterrently affects the economic activity of by-standing economies in the US-China trade war such is in our case the economy of EA. Having said that, rising trade policy uncertainty, especially between the biggest economic players, can have deterring effects on economies on a global scale. From the policy makers perspective these results can be important to take into consideration when economies are witnessing the rise of trade protectionism.

Figure 3: Impulse responses of the EA variables to TPU shocks



In broader perspective the literature finds (general) uncertainty shocks similar to negative demand shocks as uncertainty shocks decrease economic activity and induce a negative co-movement between the responses of inflation and unemployment (Colombo, 2013; Caggiano *et al.* 2014; Nodari, 2014; Kamber *et al.* 2016; Leduc & Liu, 2016).

Taking into account the conclusions from the relevant literature we consider additional variables that disentangle TPU shocks from negative demand shocks. Based on this, our results seem to be in line with Caggiano *et al.* (2020) who find that the spillover effects of uncertainty shocks do not produce prolonged fluctuations on real variables (such as output or GDP), while they generate more negative and long-lasting contractions in inflation rates. They build upon the findings of Bachmann *et al.* (2013), Jurado *et al.* (2015) , Baker *et al.* (2016) that uncertainties produce different shock persistences on macroeconomic and financial aggregates *via* "wait and see" channel effect.

Forecast error variance decomposition. To quantify how much of the variation in EA macroeconomic variables is due to the TPU shocks, we compute the forecast error variance decomposition. In Table 3, we present the results of the forecast error variance decomposition for different horizons. In particular, next to the studied TPU shocks, we also consider a selection of other shocks, including a real, a nominal and a global shock, in order to widen the comprehension of the different nature of shocks that affect the EA economy. The four columns of Table 3 report the contribution of the induced TPU shocks, supply shocks, monetary policy shocks and global demand shocks, respectively, on EA macroeconomic variables at one year ($h = 5$) and three years ($h = 13$). Some considerations are in order. It is worth noting that the TPU shock is the main contributor to the Euro EER fluctuations either in the medium and in the long term. A share of more than 25% of Euro EER deviations is indeed to be attributed to TPU shocks.[4] On the other hand, supply shocks are important for GDP, especially in the long-run, while the contractionary monetary policy shocks can be considered as the main drivers of disinflationary dynamics. From a global point of view, the foreign demand shocks mostly impact the real domestic variables, especially in the medium term.

[4]This result does not come as a surprise as Schnabl (2008) finds that the main drivers of the exchange rate stability are stable trade, capital inflows and macroeconomic stability. Consequently, increasing (trade) uncertainty could also significantly affect the stability of the exchange rate of a particular country.

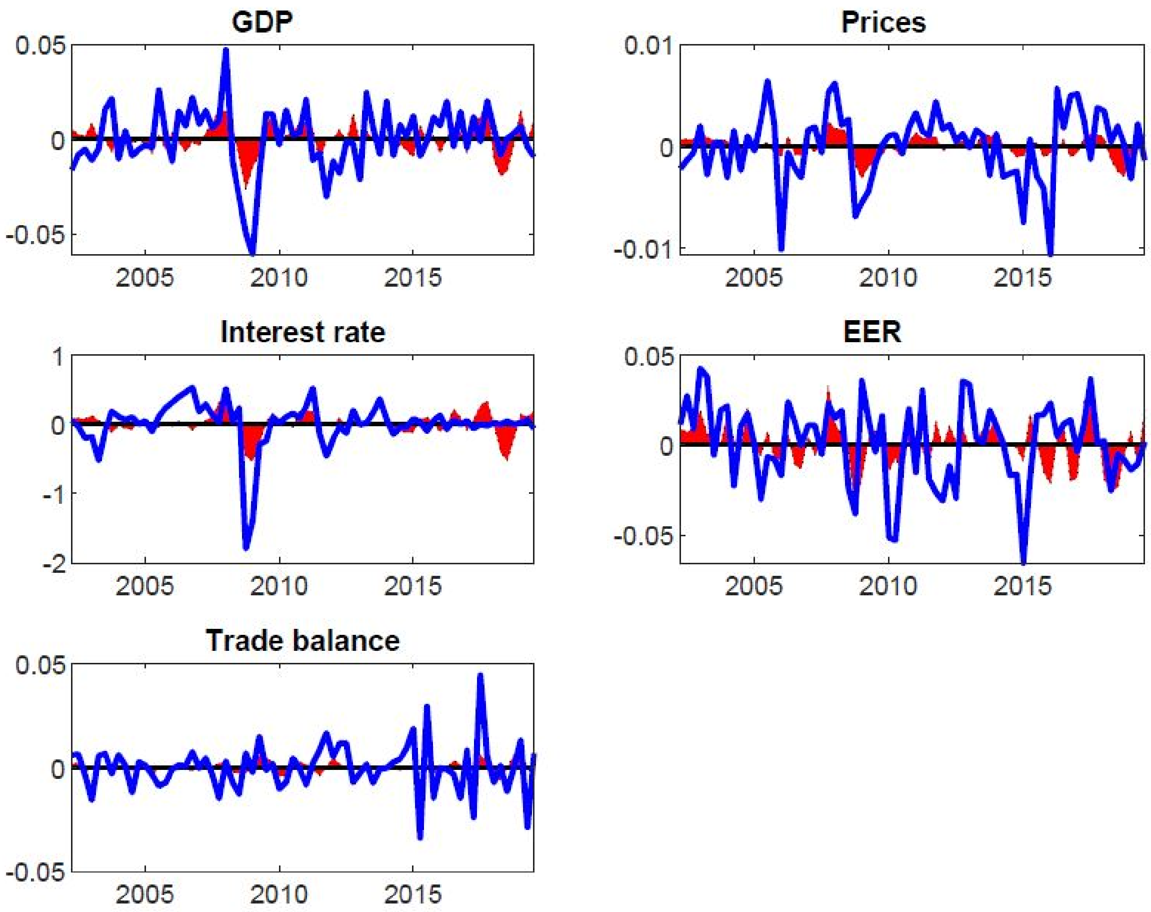
Table 3: Forecast error variance decompositions of EA variables to selected shocks

	Trade uncertainty	Supply	Monetary policy	Global demand
Variable	$h = 5$, $h = 13$	$h = 5$, $h = 13$	$h = 5$, $h = 13$	$h = 5$, $h = 13$
GDP	0.09, 0.11	0.10, 0.04	0.02, 0.03	0.35, 0.28
Prices	0.24, 0.14	0.23, 0.25	0.39, 0.40	0.03, 0.04
Interest rate	0.11, 0.09	0.07, 0.06	0.07, 0.18	0.20, 0.22
Euro EER	0.28, 0.32	0.03, 0.02	0.15, 0.15	0.09, 0.15
Trade balance	0.03, 0.04	0.44, 0.29	0.22, 0.38	0.25, 0.17

Historical decomposition. To assess the contribution of TPU shocks to the total forecast error in each point in time, the historical decomposition of each EA variable is plotted in Figure 3. Consistently with the impulse response functions and the forecast error variance decomposition, TPU shocks play an important role in explaining the volatility of the Euro EER during the Great Recession and over the last three years when the US-China trade war has significantly intensified. Non-negligible support to the Euro EER deviations is provided by TPU shocks even in the first part of the 2000s. The same story can be told for the EA prices, although the contribution of TPU shocks is smaller in this case. The GDP, interest rate and, to a much weaker extent, the trade balance show interesting reactions over the period of the Great Recession and of trade war tightening, but no significant provision is given during the other years.[5]

[5] In Appendix, in Figure A1, we also plot the TPU shock series over the sample period.

Figure 4: Contribution of TPU shocks to EA variables - historical decomposition



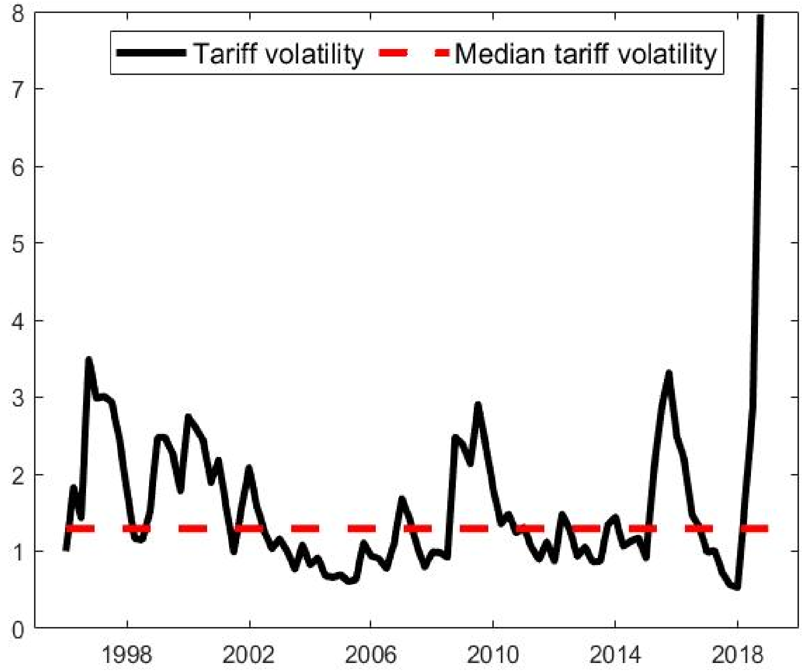
The recent trade tensions follow a gradual rise in protectionism. The number of new sovereign measures restricting global trade has increased over the past decade, while there have been relatively fewer measures favouring trade liberalization. For EA countries, the number of harmful measures implemented or announced by its trading partners has also been on the rise, potentially increasing trade costs for exporters and businesses.

3.2 Alternative specifications

Tariff volatility. In the second specification of the model we check the responses of the EA economy on the trade policy uncertainty shocks by replacing the TPU index with the tariff volatility index. Similar to the TPU index, the tariff volatility exhibits upswings of tariff uncertainty in periods of uncertainty in trade policies (Figure 5).

Again, it is clearly evident that in the recent years the onset of the US-China trade war has pushed the tariff volatility index above its historical median.

Figure 5: Tariff volatility index

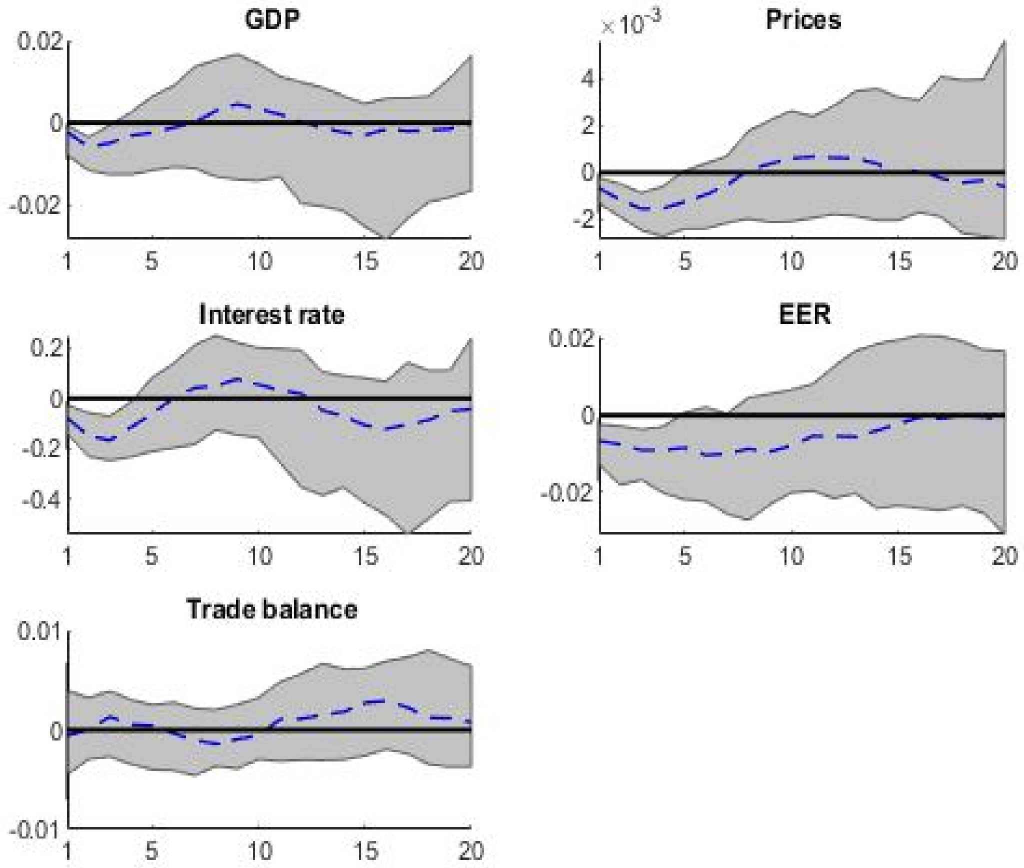


Source: Caldara et al. (2020)

In this case the identification strategy of the model stays the same as in the baseline case.[6] The results of the model with tariff volatility offer similar conclusions as in the baseline model. Figure 6 shows the median impulse response functions with the 68% credible interval of the main EA macroeconomic variables to a tariff volatility shock. As in the baseline model, the responses of the GDP and the interest rate to a tariff volatility shock are stronger but less persistent in comparison to the responses of the Euro EER and prices. Considering the alternative specification of the model by using the tariff volatility index variable we are ale to produce similar results to the baseline model and thus confirm the conclusions made by Caggiano *et al.* (2020) with respect to the effects of uncertainty shocks on the nominal and real variables.

[6]We follow the sign restriction matrix of the identified shocks from the Table 1.

Figure 6: Impulse response functions of the EA variables to tariff volatility shocks

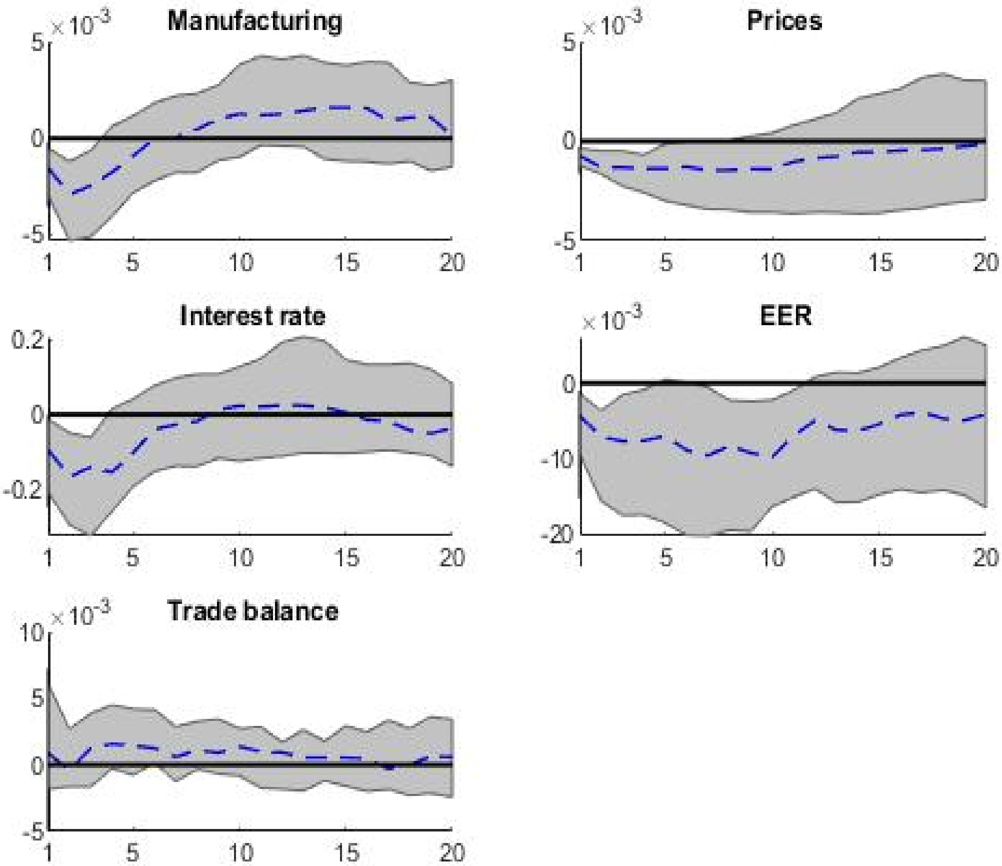


As in the baseline model, we compute the forecast error variance decomposition for the model with tariff volatility (see Table A1 in the Appendix) and assess the contribution of tariff volatility shocks to the total forecast error in each point in time with the historical decomposition of each EA variable (see Figure A2 in the Appendix).

To test the informational content of the variables employed as proxies for trade policy uncertainty, i.e. the news-based index of aggregate TPU and the tariff volatility index, we run the Granger-causality test based on bivariate VAR(4). On one hand, we find that there are no evidence the news-based index of aggregate TPU to be Granger-caused by the tariff volatility index (p-value $= 0.86$). On the other hand, the outcomes suggest that we can reject the null hypothesis aggregate TPU does not Granger-cause the tariff volatility index (p-value $= 0.00$).

Manufacturing. We provide an additional specification of an alternative model that considers manufacturing sector as the GDP proxy of the model. We maintain the same identification procedure even for this specification. Again, we are able to produce robust results with the manufacturing model setting as the impulse response functions of the EA macroeconomic variables show statistical significant responses to trade policy uncertainty shocks (Figure 7).

Figure 7: Impulse response functions of the EA variables to TPU shocks - manufacturing.



We also compute the forecast error variance decomposition, that shows variation in EA macroeconomic variables is due to the TPU shocks (see Table A2 in the Appendix). Based on this, the contribution of TPU shocks to the total forecast error in each point in time, the historical decomposition of each EA variable plotted in Figure A3 in the Appendix shows that the TPU shocks play an important role in explaining the volatility of the macroeconomic EA variables.

4 Conclusions

Based on a number of developments in the global geo-political environment, the role of the (trade) policy uncertainty raised discussions amongst researchers. The Brexit vote, the height of the sovereign debt crisis in Europe and the outbreak of the US-China trade war are one of the most important factors that have shaped the economic activities in recent years. In this paper we analyse the response of the EA business cycle to the trade policy uncertainty shocks by estimating a number of structural shocks, which are identified with a minimum set of sign restrictions in a Bayesian VAR model setting.

The empirical results suggest that TPU shocks do have significant effects on the EA economy, especially on prices and mostly on the Euro EER in the long-term. Output and interest are also affected but their responses are sharper but last only for a couple of quarters. To confirm our findings from the baseline model, we set up alternative specifications. In the first one, we replace the TPU index with a different measure, the tariff volatility. In the second one, we use manufacturing as a proxy for GDP. Both alternatives are robust. Moreover, we also show that TPU shocks have a non-homogeneous magnitude on the real economy, according to the sector that we consider.

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Appendix A

Figure A1: TPU shock over the sample period

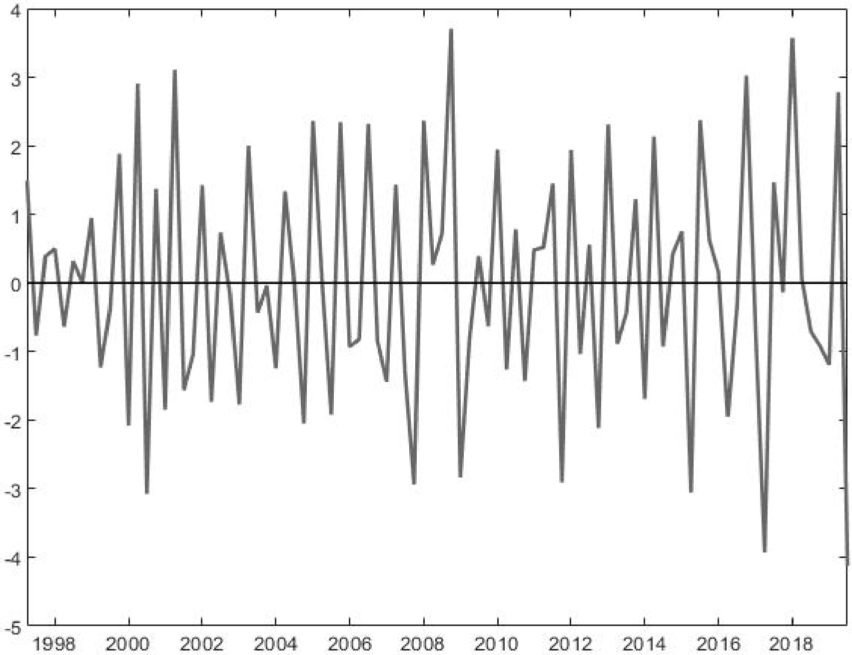


Table A1: Forecast error variance decompositions of EA variables to selected shocks - alternative model with tariff volatility

	Trade uncertainty	Supply	Monetary policy	Global demand
Variable	$h = 5$, $h = 13$	$h = 5$, $h = 13$	$h = 5$, $h = 13$	$h = 5$, $h = 13$
GDP	0.10, 0.06	0.23, 0.14	0.03, 0.06	0.17, 0.13
Prices	0.26, 0.14	0.11, 0.18	0.41, 0.41	0.03, 0.13
Interest rate	0.13, 0.12	0.21, 0.20	0.02, 0.08	0.08, 0.10
Euro EER	0.14, 0.23	0.04, 0.03	0.18, 0.20	0.09, 0.10
Trade balance	0.02, 0.04	0.37, 0.25	0.19, 0.33	0.37, 0.27

Figure A2: Contribution of TPU shocks to EA variables - historical decomposition (tariff volatility)

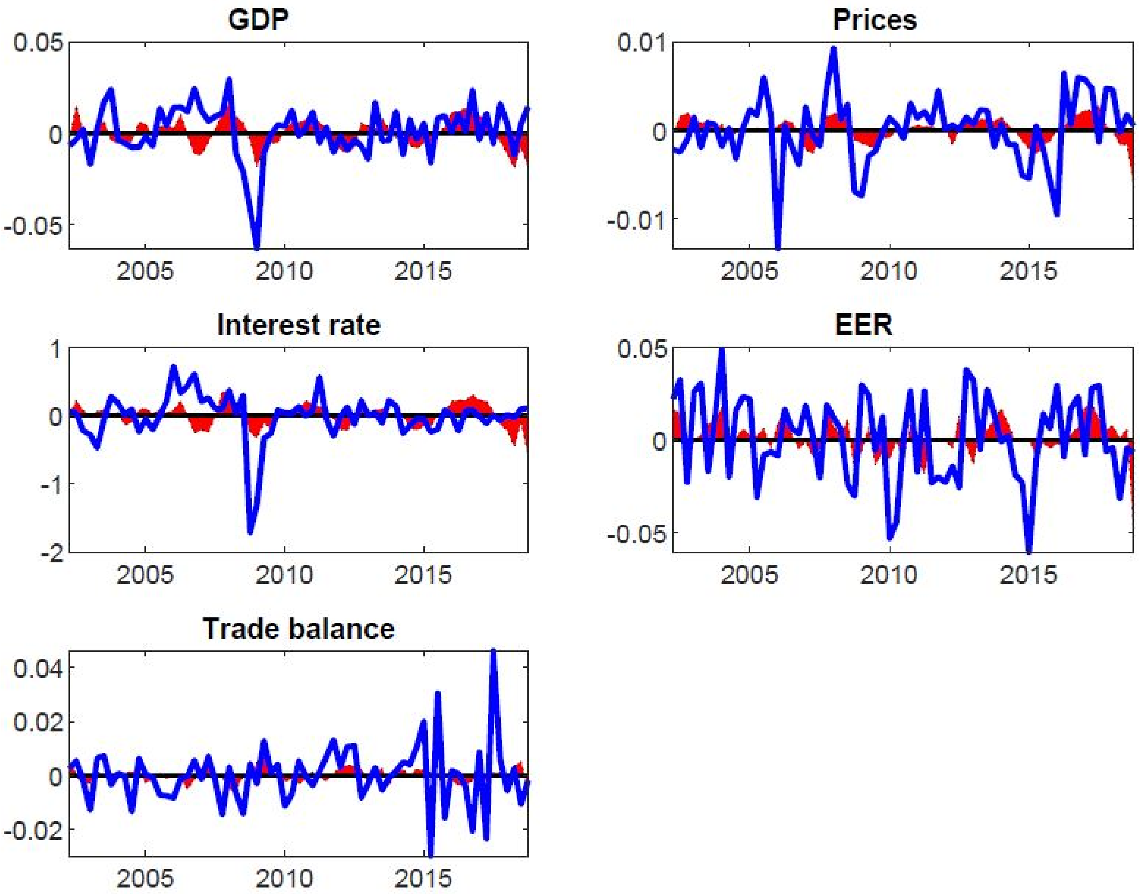
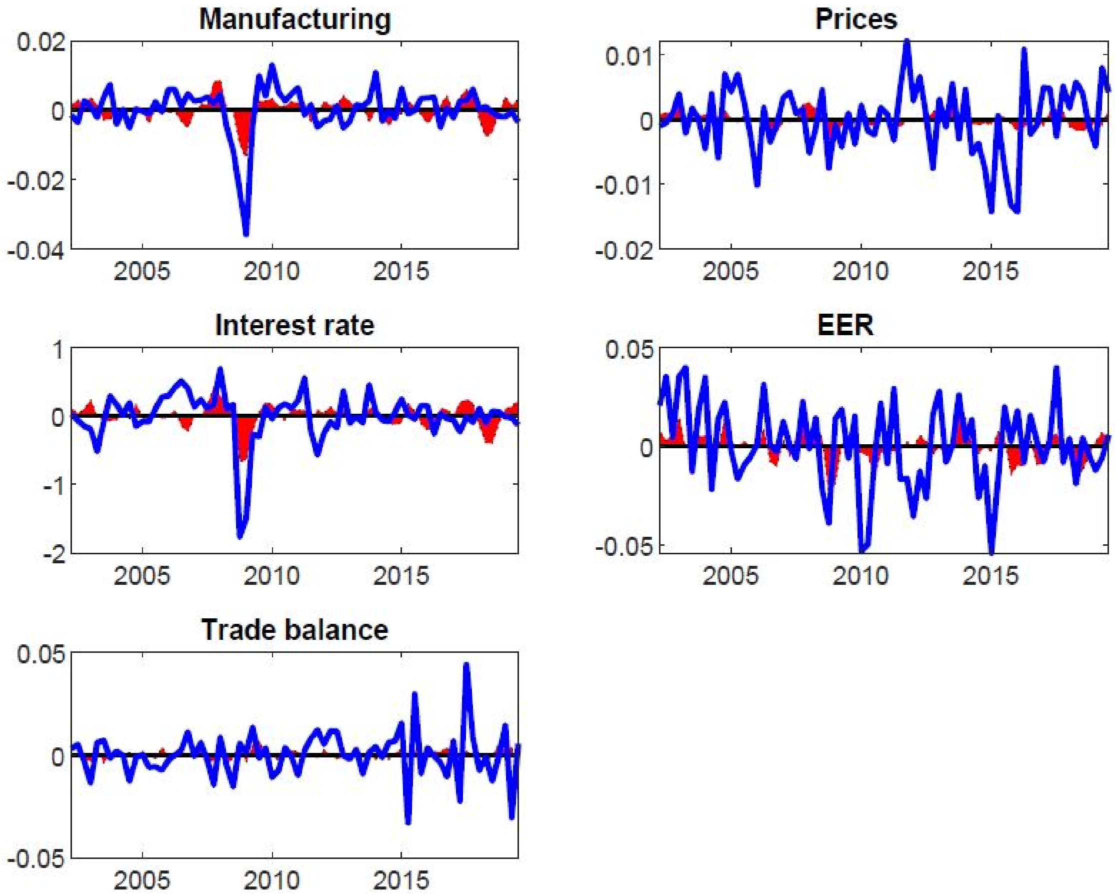


Table A2: Forecast error variance decompositions of EA variables to selected shocks - alternative model with manufacturing

	Trade uncertainty	Supply	Monetary policy	Global demand
Variable	$h = 5$, $h = 13$	$h = 5$, $h = 13$	$h = 5$, $h = 13$	$h = 5$, $h = 13$
Manufacturing	0.16, 0.12	0.15, 0.12	0.01, 0.02	0.28, 0.18
Prices	0.24, 0.12	0.32, 0.47	0.34, 0.23	0.03, 0.01
Interest rate	0.18, 0.12	0.14, 0.12	0.09, 0.17	0.18, 0.18
Euro EER	0.10, 0.21	0.06, 0.05	0.14, 0.15	0.10, 0.11
Trade balance	0.04, 0.05	0.53, 0.48	0.14, 0.17	0.20, 0.13

Figure A3: Contribution of TPU shocks to EA variables - historical decomposition (manufacturing)



Appendix B

We report here details of the estimation procedure. We closely follow Furlanetto *et al.* (2019).

We rewrite the VAR model in (1) in its compact way:

$$Y = BX + U \tag{3}$$

where $Y = [y_1 \dots y_T]'$, $B = [CB_1 \dots B_p]'$, $U = [u_1 \dots u_T]'$, and

$$X = \begin{bmatrix} 1 & y'_0 & \cdots & y'_{-p} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & y'_{T-1} & \cdots & y'_{T-p} \end{bmatrix} \tag{4}$$

The compact VAR model presented in (3) can be rewritten in its vectorized form:

$$y = (I_N \otimes X) \tag{5}$$

where $vec()$ stands for columnwise vectorization, $y = vec(Y)$, $\beta = vec(B)$, and $u = vec(U)$. We assume error term to be normally distributed with zero mean and variance-covariance matrix equal to $\Sigma \otimes I_T$.

The likelihood function in B and Σ is

$$L(B, \Sigma) \propto |\Sigma|^{-\frac{T}{2}} exp\{-\frac{1}{2}(\beta - \hat{\beta})'(\Sigma^{-1} \otimes X'X)(\beta - \hat{\beta})\} \exp\{-\frac{1}{2} tr(\Sigma^{-1} S)\} \tag{6}$$

where $S = ((Y - X\hat{B})'(Y - X\hat{B}))$ and $\hat{\beta} = vec(\hat{B})$ with $\hat{B} = (X'X)^{-1}X'Y$. We assume diffuse priors so that the information in the likelihood is dominant and these priors lead to a Normal-Wishart posterior. In more detail, we use a diffuse prior for β and

Σ that is proportional to $|\Sigma|^{-\frac{n+1}{2}}$. The posterior is then

$$p = (B, \Sigma|Y, X) \propto |\Sigma|^{-\frac{T+n+1}{2}} exp\{-\frac{1}{2}(\beta - \hat{\beta})'(\Sigma^{-1} \otimes X'X)(\beta - \hat{\beta})\} \exp\{-\frac{1}{2}tr(\Sigma^{-1}S)\} \tag{7}$$

The posterior in (3) is the product of a normal distribution for β conditional on Σ and an inverted Wishart distribution for Σ (see, e.g. Kadiyala and Karlsson, 1997 for the proof). We then draw β conditional on Σ from

$$\beta|\Sigma, Y, X \sim N(\hat{\beta}, \Sigma \otimes (X'X)^{-1}) \tag{8}$$

and Σ from

$$\Sigma|Y, X \sim IW(S, v) \tag{9}$$

where $v = (T - n) * (p - 1)$ and N representing the normal distribution and IW the inverted Wishart distribution.