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Uncertainty and the US economy: An investigation of the economic effects of economic policy uncertainty shocks originating in the US and Europe

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Abstract

This paper investigates the effect of economic policy uncertainty shocks originating in the US and four major European economies (France, Germany, Italy and the UK) on US employment and industrial production. Using Baker et al. (2016)'s newspaper-based EPU indices to quantify economic policy uncertainty, and monthly macroeconomic data from January 1987 to December 2015, vector autoregressive models and smooth transition vector autoregressive models are estimated to model the dynamic relationship between economic policy uncertainty and macroeconomic variables. Estimates of dynamic effects of uncertainty shocks are obtained by constructing (generalised) impulse response functions. In order to recover orthogonal shocks, this paper uses external instruments in a new instrumental variable approach alongside standard Cholesky decompositions. External instruments are constructed by using a dynamic factor model for EPU indices from multiple countries to estimate latent common and country-specific uncertainty factors. By replicating the results of Baker et al. (2016), it is confirmed that domestic economic policy uncertainty shocks can have negative effects on the employment level and the industrial production level in the US. Extending the analysis, it is found that domestic economic policy uncertainty shocks are also followed by decreases in the growth rates of employment and industrial production during both recessions and expansions. Further, it is found that while there is significant evidence of spillovers of European economic policy uncertainty into US economic policy uncertainty, these are very small in magnitude. When considering direct economic effects of increased European economic policy uncertainty, only shocks to French economic policy uncertainty are found to be followed by decreases in US economic growth, while shocks to economic policy uncertainty in Germany, Italy and the UK trigger no significant responses.

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Contents

1 Introduction

The great recession of 2008 and the role of uncertainty therein sparked a surge of academic interest in the economic effects of uncertainty. Today, this may be more relevant than ever: economic policy uncertainty, as measured by the newspaper-based *EPU* indices of Baker et al. (2016), has reached record-high levels over the last years. The election of President Trump in November 2016, for example, resulted in values of the EPU index of the United States (US) that even exceeded the levels measured during the financial crisis. This alone could be reason for concern if economic policy uncertainty in the US indeed had negative economic effects. In addition, such concerns are aggravated by the fact that in the EPU indices for France, the United Kingdom (UK) and Europe as a whole, 2016 and 2017 were the years with highest mean economic policy uncertainty in more than 20 years. Considering ongoing negotiations on Brexit, the European refugee crisis and the resulting rise of nationalistic parties in many European countries, this observation may not be surprising. Given the close interconnectedness of the global economy, it seems plausible that these surges in uncertainty in Europe could have economic effects also in the US; in particular because the European Economic Area is the largest trading partner of the US, and in 2017 France, Germany, Italy and the UK were among the top 10 countries with most bilateral trade with the US (Roberts, 2018). Given current elevated levels of economic policy uncertainty, it thus seems to be of particular relevance to investigate not only whether US economic policy uncertainty has domestic economic effects, but also whether economic policy uncertainty in Europe has effects on uncertainty and economic outcomes in the US.

As shown by, for example, Baker et al. (2016), economic policy uncertainty shocks within a country can have significant domestic economic consequences, and decrease the levels of employment and industrial production. Further, Caggiano et al. (2017a) find that domestic economic effects of such economic policy uncertainty shocks are more pronounced during periods of recessions than expansions. Economic policy uncertainty also tends to spill over from one country to the next (Klößner and Sekkel, 2014), especially when the degree of bilateral trade is high (Balli et al., 2017). The direct effect of US uncertainty on economic outcomes in other countries has been thoroughly investigated, and it is found that economic policy uncertainty shocks in the US indeed have an adverse effect on European economies (Colombo (2013), Stockhammar and Österholm (2017)). Investigations into the effects of international economic policy uncertainty on US macroeconomic variables, on the other hand, are very limited. Fontaine et al. (2017) find that Chinese economic policy uncertainty has negative macroeconomic effects in the US only during recessions, and Netšunajev and Glass (2017) find no effect of European economic policy uncertainty on US macroeconomic variables in either stage of the business cycle.

This paper aims to add to current literature and extend on the findings of Baker et al. (2016), by investigating whether economic policy uncertainty shocks originating in the US and in the four largest European economies – France, Germany, Italy and the UK – have an effect on economic outcomes in the US. For this purpose, monthly data from 1987 to 2015 is used to examine the effect of economic policy uncertainty, measured by the newspaper-based EPU indices of Baker et al. (2016), on the levels and growth rates of employment and the industrial production index in the US. Next to the linear vector autoregressive (VAR) model used by Baker et al. (2016), the dynamic relationship between the considered variables is also modelled using a smooth transition vector autoregressive (STVAR) model to allow for different dynamics throughout the business cycle. Estimates of dynamic effects of uncertainty shocks are then obtained by constructing (generalised) impulse response functions. Instead of relying only on exogeneity conditions to identify orthogonal shocks to economic policy uncertainty, this paper makes use of a new tool for identification. In an approach recently formalized by Stock and Watson (2018), external instruments are used for identification in addition to standard Cholesky decompositions. To create series of external instruments, a dynamic factor model is used to decompose international EPU series into common components as well as country-specific uncertainty. By doing so, this paper makes multiple contributions to academic discourse. First, new insights into the dynamic relationship between US macroeconomic time-series and economic policy uncertainty shocks originating in the US and Europe are provided. Second, to the best of my knowledge, this paper is one of the first to explore the suitability of different types of instruments to identify exogenous shocks to uncertainty. Third, the dynamic factor model applied in this paper provides new insights into the distinction between world-wide and country-specific economic policy uncertainty.

The investigations in this paper bring multiple interesting results. By replicating the findings of Baker et al. (2016), it is confirmed that increased economic policy uncertainty in the US can have negative effects on domestic employment levels and the industrial production index. In extensions of the analysis, evidence for cointegration between the considered series is found, indicating that these effects may even be permanent. Further, heightened domestic economic policy uncertainty in the US also has a negative impact on the growth rates of the considered series, both during recessions and expansions. When considering economic policy uncertainty shocks originating in France, Germany, Italy and the UK, significant evidence that these can trigger increases in economic policy uncertainty in the US is found. Nevertheless, these increases are of negligible magnitude for all four European countries. In addition, these economic policy uncertainty shocks can be related to worsened economic performance of the domestic economy of France and Germany, yet significant evidence that this also followed by negative effects on US economic variables is only found for shocks originating in France. For the UK and Italy, there is no significant evidence that shocks in EPU have any economic effects.

This paper proceeds as follows: Section 2 presents a short overview of previous literature investigating the effects of domestic uncertainty on macroeconomic activity and the existence of uncertainty spillover effects. Section 3 introduces the available data. Section 4 elaborates on strategies for identification of exogenous economic policy uncertainty shocks, which includes the estimation of a dynamic factor model as well as a discussion of the exogeneity of different types of shocks. Section 5 discusses the basic vector autoregressive model employed in this paper, its extension to incorporate business cycle effects, identification of orthogonal shocks, and impulse response analysis. Section 6 presents a replication and discussion of Baker et al. (2016)'s results concerning the effects of US economic policy uncertainty on economic level-series as well as the results of the extended analysis concerning the effects of domestic and European policy uncertainty shocks on US economic growth. Section 7 contains the conclusion and discussion of limitations of this research.

2 Literature review

This section discusses the findings of previous research and their implications for the investigation at hand. First, literature arguing why, in theory, domestic uncertainty matters for macroeconomic outcomes is reviewed and the empirical findings of Baker et al. (2016) and others with respect to the effect of uncertainty are discussed. Second, findings with respect to spillover of economic policy uncertainty and macroeconomic spillover effects are considered.

2.1 Economic effects of domestic uncertainty

Theoretical literature proposes multiple channels through which uncertainty in general could lead to adverse economic effects. Bloom (2014) provides a comprehensive literature review of such channels, which are shortly summarized here. First, high uncertainty increases the value of 'real options', that is, the ability to delay investment when uncertainty about future payoffs is high. On the supply side, this may result in reduced investment in capital as well as postponing hiring new employees. On the demand side, consumers will delay some purchases due to uncertain future income and economic conditions. Therefore, Leduc and Liu (2016) propose that uncertainty shocks essentially have the same effect as an aggregate demand shock: uncertainty reduces aggregate demand, thus firms offer fewer jobs, which decreases demand and the price level even further. Second, increasing uncertainty may lead to higher risk premia for investors and hence the cost of raising capital will increase, reducing overall investment. Third, uncertainty makes individuals less confident in their predictions, which may induce phenomena like precautionary savings to surge.

These theoretical predictions of adverse effects of uncertainty have been tested in numerous empirical studies, which consider different types of uncertainty, different measures for uncertainty and different levels of aggregation of economic data. Heightened uncertainty about future policy in election years, for example, has been used to identify adverse effects of policy uncertainty on initial public offerings (IPOs), investor price sensitivity, investments, and foreign direct investment (FDI) (by Çolak et al. (2017), Gulen and Ion (2015), Julio and Yook (2012) and Julio and Yook (2016), respectively). Baker and Bloom (2013) use the timing of natural disasters, terrorist attacks and political coups to show that uncertainty shocks in general reduce economic growth. Bloom (2009) and Leduc and Liu (2016) find similar results using the stock market volatility index (VIX) and consumer survey data, respectively, as proxies for uncertainty. Fernández-Villaverde et al. (2015) show that uncertainty about fiscal policy, such as taxation, also has negative effects on economic activity.

Baker et al. (2016) propose a newspaper-based index, the EPU index, which aims to directly capture the level of economic policy uncertainty in a country. The index is based on the frequency at which articles related to economic policy uncertainty appear in national newspapers, and is constructed for the US and multiple other countries. They use this index to investigate domestic effects of economic policy uncertainty at firm-level and aggregate level in the US, and their results are in line with research using other measures for uncertainty. At the firm level, they find that economic policy uncertainty can be related to greater stock price volatility, lower investment and lower employment growth for firms with high exposure to government financing. At the aggregate level, employment and industrial production are reduced significantly in response to an uncertainty shock.

Many empirical investigations have also shown that key US macroeconomic time-series, such as employment, exhibit non-linear behaviour changes over the business cycle (for example, Koop and Potter (1999)). It therefore seems likely that the dynamic relationship between uncertainty and macroeconomic outcomes also differs between recessions and expansions. The findings of Caggiano et al. (2014) and Caggiano et al. (2017a) support this proposition empirically. Respectively, they investigate the effects of uncertainty in general, proxied by the VIX, and economic policy uncertainty, proxied by the EPU index, using smooth transition vector autoregressive models. Both find that uncertainty shocks have a larger adverse effect on employment and other macroeconomic series during recessions than during expansions.

The theoretical prediction that higher uncertainty leads to postponement of hiring decisions and reduced (investment) demand, and the empirical support provided by the findings discussed above, lead to the hypothesis for this investigation that domestic economic policy uncertainty shocks have a negative effect on both employment and industrial production in the US. Further, given the findings of Caggiano et al. (2017a), these effects are expected to be more pronounced during business cycle downturns.

2.2 International effects of economic policy uncertainty

Given the empirical evidence indicating domestic economic effects of economic policy uncertainty, some studies have turned to examine whether there is spillover of uncertainty of one country to another. On the one hand, it is investigated to what extent heightened economic policy uncertainty in one country leads to heightened economic policy uncertainty in others, which could, for example, be the result of uncertainty about the continuance of important trade relationships. Klößner and Sekkel (2014) find that there is significant spillover between the US and five other countries, where the US and the UK mostly act as 'exporters' of economic policy uncertainty, and that such spillover acts very counter-cyclically. Balli et al. (2017) also find significant spillovers, and conclude that the magnitude of spillover effects are indeed positively related to the amount of bilateral trade between countries.

On the other hand, some studies investigate directly whether uncertainty in one country also affects macroeconomic outcomes of another. It is found that US economic policy uncertainty shocks have adverse macroeconomic effects in other countries and regions, for example in Canada (Caggiano et al., 2017b), the Euro area (Colombo, 2013) and Skandinavia (Stockhammar and Österholm, 2017). Most such literature, however, has focused on the effect of US economic policy uncertainty on other countries, while the effect of foreign uncertainty on US macroeconomic variables has largely been neglected. Only macroeconomic effects of Chinese economic policy uncertainty on US variables during economic downturns have been found (Fontaine et al., 2017). Netšunajev and Glass (2017) investigate whether European economic policy uncertainty shocks have macroeconomic effects in the US, but find no empirical evidence that this is the case.

When considering why, in theory, economic policy uncertainty in Europe could have an adverse macroeconomic effect in the US, there are two distinct channels to examine. First, there could be a pure uncertainty spillover channel. Heightened European economic policy uncertainty might lead to adverse effects on the US economy due to increased US uncertainty, about, for example, trade relationships. As discussed above, any such uncertainty shock can reduce demand and investment within the US. Thus, if a shock to European uncertainty increases uncertainty in the US, this may have adverse economic effects in the US.

Even if the US does not "import" policy uncertainty from other countries, economic policy uncertainty shocks in Europe could still have negative economic effects in the US through a second channel. An economic policy uncertainty shock in Germany, for example, could cause a German economic downturn, which may propagate to the US through a purely economic channel. German firms, investors and consumers could reduce their own demand as a result of heightened uncertainty as argued by Leduc and Liu (2016). If, for example, this induces lower import demand for US goods, lower foreign (direct) investment or lower returns to US investment in Germany, there could be a direct adverse effect on the US economy as a result of German uncertainty. More generally, if such a negative uncertainty shock causes an economic downturn in Germany, this may spillover to the US economy due to international business cycle linkages. Numerous previous studies have investigated the synchronization of international business cycles, and have found evidence of business cycle spillovers (for example, Canova et al. (2007) and Yilmaz (2010)).

Given the importance of the trade relationship between European countries and the US, this paper hypothesizes the existence of such uncertainty channels and economic channels, despite the current lack of empirical evidence. Additionally, as Fontaine et al. (2017) and Klößner and Sekkel (2014) find evidence that spillovers of uncertainty act very counter-cyclically, it is expected that negative economic effects of European uncertainty shocks are more visible during recessions than during expansions.

3 Data

Economic policy uncertainty in the US (EPU_t^{US}) is measured by Baker et al. (2016)'s newspaper-based EPU index. It counts the number of articles mentioning a trio of terms from the categories *uncertainty*, *economy* and *policy* in 10 major US newspapers in a given month, scaled by the total number of articles in each newspaper. Note that the index has been altered since the publication of their paper[1], and that the newer version of the index, which is currently available from Baker et al. (2018), will be used in this paper. Similarly, the EPU indices for Germany, France, Italy and the UK, will be used to model uncertainty in the European countries. The

[1] It is unclear which version of their index Baker et al. (2016) used in their paper. As the authors made their dataset available, I could cross-check their data with published versions of their index, however, it seems that this data is not exactly equal to any other published (older instances) of their index. Using the new instance of the index has no significant impact on the baseline results of Baker et al. (2016). The point estimates of the impulse responses in early periods are slightly smaller in magnitude, yet these changes are well within the confidence bands. A comparison of results using the two datasets are shown in Figure A.1 in Appendix A.

indices for these countries are based on the scaled number of articles mentioning terms from all three search sets (in the native language) published in two major national newspapers. All these indices were retrieved from Baker et al. (2018). Whenever this paper mentions "EPU", this refers to the newspaper index constructed by Baker et al. (2016)[2].

To follow Baker et al. (2016) in their approach, this paper considers the effect of shocks in uncertainty on log-transformed employment ($log(emp_t)$) and the log-transformed industrial production index ($log(IP_t)$) to identify macroeconomic effects, while controlling for movements in the log-transformed S&P500 index ($log(S\&P500_t)$) and the effective federal funds rate (FFR_t). Due to the forward-looking nature of stock markets, the S&P500 index should control for (negative) information about the future economy that is already anticipated(Baker et al., 2016), while the effective federal funds rate controls for US monetary policy(Caggiano et al., 2017d). Data for these variables up to October 2014 was made available by the authors. To extend the horizon, updated data is retrieved for employment(U.S. Bureau of Labor Statistics, 2018), IP (Board of Governors of the Federal Reserve System (US), 2018b), the S&P500 index (Shiller, 2018) and the effective federal funds rate (Board of Governors of the Federal Reserve System (US), 2018a). To control for the state of the economy in the European countries, data on their industrial production indices is obtained (OECD, 2018) and included in log-transformed form, which can also be used to trace responses of the domestic economies to European EPU shocks. Ideally, further control variables similar to those for the US should be included for the European countries, too, however, the considered vector autoregressive models would become very large which would be problematic for estimation. As the effect on US economic variables is of main interest in this paper, the responses of domestic IP will only be considered tentative evidence for domestic effects of economic policy uncertainty in Europe.

Except when replicating Baker et al. (2016)'s results, the main analysis of this paper uses series that are weakly stationary to avoid issues related to non-stationarity. The previously mentioned macroeconomic time-series are tested for a unit root using the augmented Dickey-Fuller test, and the presence of a unit root cannot be rejected for any of them. Therefore, first differences of the macroeconomic time-series are considered instead of their levels. First differences of log-transformed series can be interpreted as growth rates of the original series, which are multiplied by 100 to allow for interpretation in percent. Using growth rates instead of level series also has an advantage for interpretation of results. Given that a majority of macroeconomic level series are continuously growing over time, responses in the levels of these series are difficult to interpret and compare over a longer time period. Growth rates generally allow for better comparison of economic effects over time and between countries. Within related literature, most papers do indeed use macroeconomic growth rate series for their investigations of economic effects of EPU, for example Caggiano et al. (2017a), Caggiano et al. (2017b) and Fontaine et al. (2017).

Additionally, monthly data on US exports to France, Germany, Italy, and the UK are obtained(U.S. Bureau of Economic Analysis and U.S. Bureau of the Census, 2018) to empirically investigate whether European EPU shocks trigger reductions of import demand from Europe.

[2]Note that this index has been available online already prior to the publication of their paper in 2016, thus some papers published before have also used it.

Table 1: Summary statistics

Variable	Mean	SD	Sample	Variable	Mean	SD	Sample
EPU series				*European IP growth*			
EPU_t^{US}	108.12	40.18	1987-2015	$\Delta log(IP_t^{FR}) \times 100$	0.059	1.346	1987-2015
EPU_t^{FR}	123.88	74.51	1987-2015	$\Delta log(IP_t^{GER}) \times 100$	0.135	1.556	1993-2015
EPU_t^{GER}	113.03	51.86	1993-2015	$\Delta log(IP_t^{IT}) \times 100$	-0.069	1.468	1997-2015
EPU_t^{IT}	108.75	38.65	1997-2015	$\Delta log(IP_t^{UK}) \times 100$	-0.043	0.924	1997-2015
EPU_t^{UK}	133.76	83.84	1997-2015				
US variables				*Export growth*			
$\Delta log(Empl_t) \times 100$	0.087	0.25	1987-2015	$\Delta log(exp_t^{FR}) \times 100$	0.434	6.85	1987-2015
$\Delta log(IP_t^{US}) \times 100$	0.16	0.63	1987-2015	$\Delta log(exp_t^{GER}) \times 100$	0.317	5.77	1993-2015
$\Delta log(SP500_t) \times 100$	0.60	3.68	1987-2015	$\Delta log(exp_t^{IT}) \times 100$	0.340	9.76	1997-2015
ΔFFR_t	-0.02	0.19	1987-2015	$\Delta log(exp_t^{UK}) \times 100$	0.288	8.16	1997-2015

This table presents summary statistics for the series used in this paper. SD stands for standard deviation. exp stands for exports from the US to the individual countries. GER denotes Germany, IT denotes Italy, FR denotes France.

As the export data are the only macroeconomic series that are not already obtained in seasonally adjusted form, they are seasonally adjusted prior to use[3]. The export series are then log-transformed, first-differenced and multiplied by 100, such that export growth rates ($\Delta log(exp_t^i)$) can be considered in this paper[4].

Both EPU and macroeconomic data are available at a monthly frequency. The beginning of the sample that is considered in this paper differs per country and ends in December 2015. The beginning is dictated by the availability of the European EPU indices: the French index is available from January 1987, while the German EPU index becomes available in January 1993, and the British and Italian indices in January 1997. Whenever US variables are considered without including any European variables, the beginning of the US sample is chosen to be January 1987 to match the length of the longest European sample. The end of all samples is chosen to be December 2015, to exclude the period of unprecedented high uncertainty since Brexit and the election of President Trump in 2016. Summary statistics for all variables are presented in Table 1.

4 Identification of exogenous shocks to economic policy uncertainty

In this section, strategies to identify exogenous variation or shocks in EPU indices are discussed, while Section 5 will discuss how these exogenous shocks are used in the dynamic analysis. Identification of exogenous shocks is necessary, because in the time span of one month – which is the horizon considered in this paper – shocks affecting any of the considered variables could plausibly cause a contemporaneous response in any of the others. Therefore, it is impossible to identify the origin of a shock that affects multiple variables in the same period without further investigation.

Generally, identification of the origin of simultaneous shocks in vector autoregressive models can

[3]The data are seasonally adjusted by using the *seasonal* package in R, which implements X-13ARIMA-SEATS, the seasonal adjustment software developed by the United States Census Bureau.

[4]For notational convenience, the indication that growth rates were multiplied by 100 is omitted in further notation. Nevertheless, all growth rates were multiplied by 100.

be achieved using two methods, which Stock and Watson (2018) refer to as internal instruments and external instruments. Internal instruments achieve identification through the placement of (exclusion) restrictions on contemporaneous relationships, which are based on findings of previous research or logical reasoning. Arguably the most common way of identification is using Cholesky decompositions, which essentially reduce to a somewhat arbitrary imposition of exclusion restrictions: shocks to the variable ordered first in the system are assumed to contemporaneously affect all other variables, but be affected by none, whereas the second variable is affected only by the first, but not by any other shocks, and so forth. Identification of dynamic responses is hence contingent on the ordering of variables and the ability to set meaningful exclusion restrictions (Ramey, 2016). In the given context, when considering the dynamics between EPU^{US} and EPU^{UK}, for example, such exclusion restrictions are not straightforward. Shocks in either variable could plausibly affect the level of the other contemporaneously, especially when considering a one month horizon.

This paper will therefore also consider a relatively new tool for identification of exogenous shocks recently formalised by Stock and Watson (2018): the use of external instruments. This entails using variables that are not already included in the system of variables and are correlated with only the shock of interest, to identify contemporaneous effects one variable has on others. While instrumental variables are a well-established tool in microeconometrics, their application to identification of exogenous shocks in macroeconomics is a new development (Stock and Watson, 2018). Previous literature using external instruments to identify shocks in uncertainty is hence very scarce, and almost all papers using time-series models in this context rely on Cholesky decompositions. Analysis in most related literature, for example, Baker et al. (2016), Caggiano et al. (2017a) and Fontaine et al. (2017), is performed by ordering the EPU variables first in a Cholesky decomposition. This imposes that policy uncertainty shocks can contemporaneously affect the economic variables, but cannot be affected by macroeconomic shocks. Yet, this assumption seems unrealistic as it is plausible that a large unexpected shock to employment, for example, could trigger public discussions about necessary government policy, resulting in an instantaneous EPU shock. A notable methodological exception in literature is Stock and Watson (2012), relying on external instruments, the innovations from autoregressive (AR) models of the VIX and EPU, to identify uncertainty shocks. Despite the difference in methodology, this suffers from the same potential endogeneity problem: it is questionable whether the external instruments, the AR-innovations, are truly exogenous with respect to other (macroeconomic) variables – in particular, because unanticipated shocks to macroeconomic variables may be entering the error-term in the AR-processes of uncertainty measures.

This paper constructs two new external instruments for each country's economic policy uncertainty shocks. Because of potential contemporaneous spillover of uncertainty, it is important to identify economic policy uncertainty shocks originating in the European countries to be able to determine their effects on US variables. As a first step, the movements of international EPU series are therefore decomposed into common and country-specific components. In order to do so, this paper investigates the possibility that there is "world uncertainty", which is uncertainty affecting countries worldwide, "European uncertainty" predominantly affecting countries in Europe, as well as country-specific, or idiosyncratic uncertainty, which captures policy uncertainty that matters mostly on a national level. To model this, a dynamic factor model with latent common components is adopted. Such models are often used in business cycle analysis (for example, Stock and Watson (1989)) to identify co-movements of macroeconomic series to construct, for example, coincident business cycle indicators. Although, to the best of my knowledge, such a model has not yet been used to identify co-movements across international economic policy uncertainty series, it seems to be a promising approach to isolate periods of heightened country-specific uncertainty. Only Biljanovska et al. (2017) use a comparable approach: they use an international panel-VAR to investigate the movement of a "world uncertainty" factor by using principal component analysis on the error terms of their model. Yet, they do not use the found factors in any further analysis.

This paper models country-specific uncertainty and two latent common components, "world uncertainty" and "European uncertainty" in the following dynamic factor model:

$$EPU_{it} = c_i + \gamma_i C_t^{world} + \delta_i C_t^{EU} + u_{it} + \omega_{it}, \text{ for } i \in I \text{ and } t \in \{1, \dots, T\} \tag{1}$$

$$C_{t+1}^j = \phi_{j1} C_t^j + \phi_{j2} C_{t-1}^j + \phi_{j3} C_{t-2}^j + \epsilon_{j,t+1}, \text{ for } j \in \{world, EU\} \text{ and } t \in \{1, \dots, T\} \tag{2}$$

$$u_{i,t+1} = \rho_{i1} u_{i,t} + \rho_{i2} u_{i,t-1} + \rho_{i3} u_{i,t-2} + e_{i,t+1}, \text{ for } i \in I \text{ and } t \in \{1, \dots, T\}. \tag{3}$$

Equation (1) specifies that the observed country specific EPU_{it} is determined by the state of a common "world" factor C_t^{world} that could be interpreted as capturing the level of "world uncertainty", a common "European uncertainty" factor C_t^{EU} whose coefficient δ_i is non-zero only for countries in Europe, an idiosyncratic component u_{it} that captures the country-specific uncertainty, and a constant term c_i, where $i \in I$ and I is the set of considered countries. The ω_{it} is random white noise which contaminates the signal in EPU, and could, for example, capture inaccuracies of the EPU index in measuring uncertainty due to its newspaper-based nature. If national events, e.g. a royal wedding, take up large parts of newspaper reports, then EPU might lie below actual economic policy uncertainty. Equations (2) and (3) describe how the common factors and the idiosyncratic terms evolve over time, where $\epsilon_{j,t}$ and $e_{i,t}$ are random shocks. The choice of three lags is made as this eliminates most evidence of autocorrelation in the $\epsilon_{j,t}$ and $e_{i,t}$ series, and corresponds to the lag-order chosen for the VAR-model discussed later in this paper. Here, it is explicitly assumed that the common components and idiosyncratic uncertainty evolve independently of each other. Clearly, this is a very simplistic assumption, however, this is necessary to facilitate estimation and identification of parameters. Additionally, this results in the fact that u_{it} is modelled to be a component that is completely exogenous to all other countries' uncertainty. Last, the shocks $\omega_{i,t}$, $\epsilon_{j,t}$ and $e_{i,t}$ are assumed to be mutually uncorrelated white noise sequences.

This model can be written in state-space representation with state vector

$$\xi_t = [C_t^{world}, C_t^{EU}, u_{1,t}, \dots, u_{k,t}, C_{t-1}^{world}, \dots, u_{k,t-1}, C_{t-2}^{world}, \dots, u_{k,t-2}]'$$

and be estimated using an EM-algorithm based on the Kalman filtering and smoothing equations. A complete description of the state-space representation of this model, as well as a description and derivation of the specifics of the used estimation algorithm can be found in Appendix B.1.

To obtain estimates of the parameters, of the common factors and of the idiosyncratic components in this model, EPU indices for Japan, China and Brazil are retrieved from Baker et al. (2018) in addition to US EPU and the European series from Germany, France, Italy and the UK. Figure 1 and Figure B.1 in Appendix B.2 illustrate the results from estimation of model (1) using these eight EPU series. Figure B.1 plots the demeaned EPU series against the components that are explained by the estimated factors. When considering the graph of the US, it becomes clear that the world factor is driven to a large extent by its fit with the movements in US EPU. Given the findings of Klößner and Sekkel (2014) that the US is an exporter of uncertainty, this may not be surprising. Large parts of movements in EPU in China, Germany and Italy also seem to be explained by the world factor. For France and the UK, the European factor explains a substantial part, whereas for Germany and Italy this factor explains only minuscule movements in EPU.

Figure 1 displays the smoothed estimates of the "world uncertainty", "European uncertainty" and the idiosyncratic uncertainty series for the US, Germany, France, the UK and Italy. The estimates are standardised to have mean zero and standard deviation one to allow for better comparison. In the graphs, periods of unusually high uncertainty, which are identified as having standardised value larger than 1.64, corresponding to the 95^{th} percentile of the normal distribution, are marked with a red circle. Where identification is possible, historical events or circumstances that, due to timing, are likely to have caused these spikes are indicated in the graphs. As many spikes indeed match historical events related to high policy uncertainty, the chosen approach seems suitable. The 9/11 terrorist attacks, the beginning of the Iraq war and the collapse of the Lehman brothers, for example, show as a spike in the estimated world uncertainty series. Country-specific policy uncertainty shocks like the stalemate in Italy's 2013 elections, the 2013 US government shut-down, or the Scottish Referendum to leave the UK in 2014, indeed show as spikes in the country-specific series.

Therefore, this paper uses the series of estimated idiosyncratic shocks from (3), $\hat{e_{i,t}}$, as instruments for country-specific uncertainty shocks. This method of identification of country-specific shocks does have two downsides: first, one cannot identify the origins of "world shocks" and "European shocks", $\hat{\epsilon}_{j,t}$, and hence shocks that hit EPU at time t all around the world but originated in, for example, the UK, cannot be identified as such. Second, the identified idiosyncratic shocks are arguably exogenous to the other EPU series, but may not be exogenous to the macroeconomic series investigated later. This remains a major concern and is similar to the problem illustrated above for the instrument used by Stock and Watson (2012). Thus, an approach that can isolate more exogenous movements from the idiosyncratic terms u_{it} will be discussed below. Note, however, that using these error-series as an instrument to identify exogenous shocks has a similar effect as ordering the EPU indices before the macroeconomic variables in a Cholesky decomposition: all simultaneous shocks are attributed to EPU. This approach has the advantage over the Cholesky decomposition that the constructed European

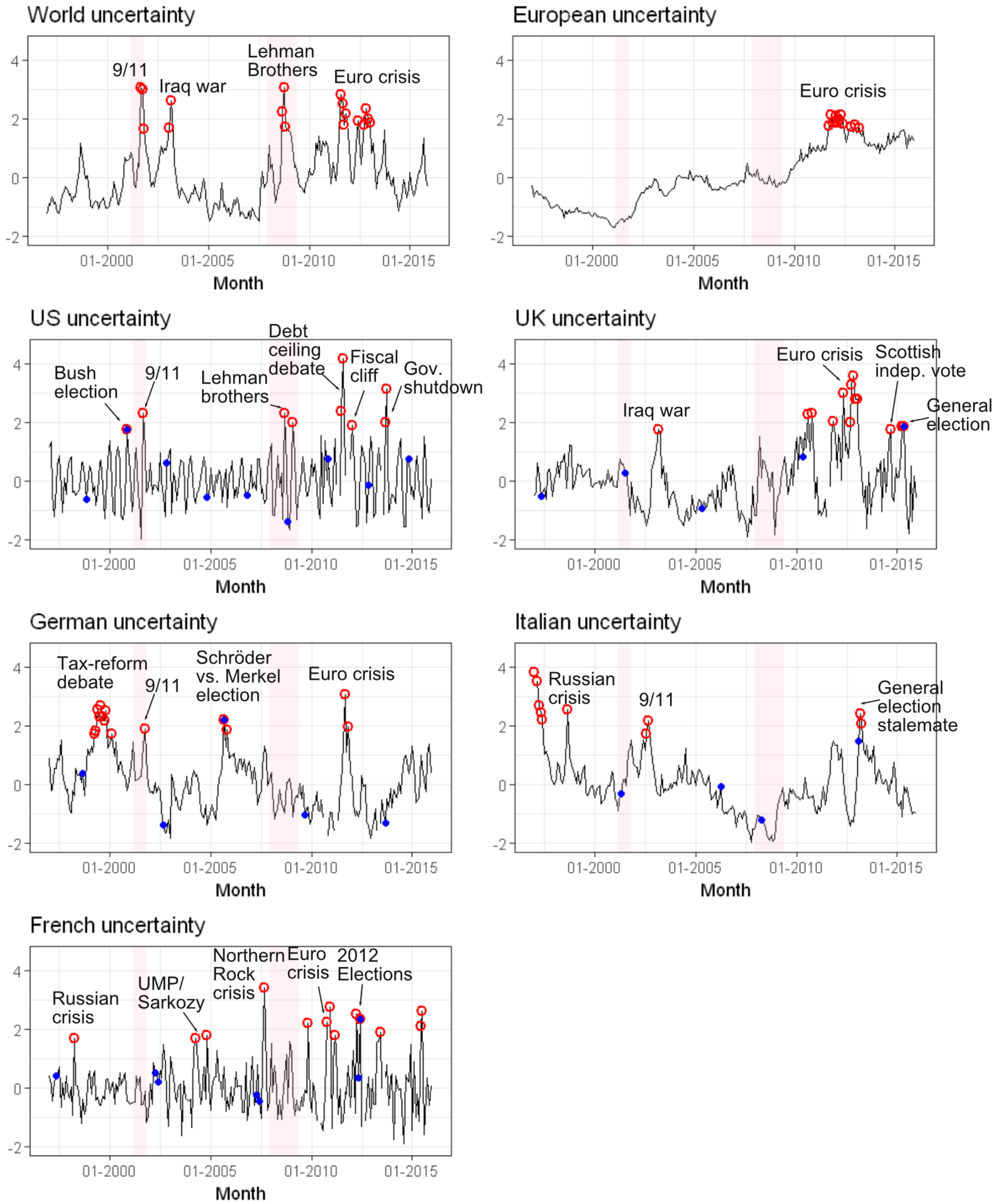


Figure 1: Smoothed estimates of standardised idiosyncratic and common factors

This figure shows smoothed estimates of the idiosyncratic and common components of the dynamic factor model presented in this section. All series are standardised to have mean zero and standard deviation one for illustrative purposes. Standardised estimates with value larger than 1.64 are indicated with a red circle. Blue (solid) dots indicate that a national election took place in that month. Red shaded areas indicate the presence of an NBER recession. Parameters and states were estimated using a sample of eight countries between 1997:01 and 2015:12.

shocks are arguably exogenous to US EPU, and hence no exclusion restriction between US EPU and other country's EPU has to be set.

Nevertheless, it is highly doubtful whether the exogeneity assumption with respect to the macroeconomic series is justified. Consider, for example, the large spikes in US uncertainty in the month of the Lehman Brothers collapse and in German uncertainty during the Euro-crisis. It is up to discussion whether these events should be regarded as economic shocks that caused an increase in EPU through their effect on the economy, or whether these were uncertainty shocks that had an impact on the economy only through increased uncertainty. For most shocks it is difficult, if not impossible to make an exact distinction. Nevertheless, it may be possible to identify some shocks which are primarily influencing policy uncertainty (as opposed to shocks that also influence the economy directly). For this, a narrative approach in the spirit of Romer and Romer (1989), Ramey and Shapiro (1998) and Ramey (2011) is necessary, which uses historical records and/or reasoning to identify shocks that are arguably exogenous.

Baker et al. (2016) define economic policy uncertainty as uncertainty about "*who* will make economic policy decisions, *what* economic policy actions will be undertaken and *when*"(Baker et al., 2016, p.1598). Therefore, by construction, national elections could be considered a source of exogenous fluctuations in economic policy uncertainty. As discussed before, such an approach has been taken by previous research to investigate firm-level effects of policy uncertainty. Nevertheless, using election timing in conjunction with EPU indices to find macroeconomic effects of policy uncertainty is problematic for two reasons. First, previous literature has found evidence for so-called political business cycles. Nordhaus (1975)'s political business cycle model predicts that politicians make policy choices stimulating the economy prior to re-elections. Some empirical evidence supporting this hypothesis has been found, although there is less evidence than theory would predict (see Drazen (2000) for a review of theoretical and empirical evidence). Second, elections will not cause spikes in the EPU index if election outcomes are anticipated and the run-up to elections have no unpredictable component, if the competing parties do not differ in their proposed economic policy, or if the press does not report on economic policy related issues. In Figure 1, the month of a national election[5] is indicated by a blue dot. It is quite obvious that most elections cannot be associated with spikes in idiosyncratic uncertainty,[6] yet, each country has one national election in the sample which is linked to extraordinarily high policy uncertainty.

As election data alone does not help to identify exogenous shocks, I attempt to reconstruct some exogenous shocks from the idiosyncratic uncertainty series directly. In order to do so, I isolate the 5% largest shocks in the $\hat{e_{it}}$ series and, if possible, match their timing to (political) events. A full list of identified shocks per country can be found in Appendix B.2. To identify events related to the uncertainty shocks, I consulted Baker et al. (2016)'s classification of large spikes in EPU as published in the online appendix of their paper. Unfortunately, many of the idiosyncratic shocks recovered here did not show as large spikes in the European EPU series, most likely because the "world uncertainty" component masked the relatively smaller movements in EPU caused by national uncertainty. For each date not identified by Baker et al. (2016), I conducted

[5] Here, national elections are defined as the parliamentary and/or presidential elections of the given country. Data on the timing of elections was obtained from the database of political institutions (DPI2015) (Scartascini et al., 2016).

[6] Initially, it was supposed to be the approach of this paper to exploit variation in EPU around national elections by using election-timing dummies with leads and lags as instruments for uncertainty shocks. Given that there is barely any substantial variation in EPU that can be attributed to elections, it is not surprising that this turned out to be a very weak instrument with a first stage F-statistic of below 1 in many cases. Therefore, this idea has been discarded.

an online search[7] into country-specific policy-related events. Where no results are found, this could have two reasons. First, national policy-related issues, especially if they took place in the early 2000s or 1990s, are difficult to track down online and in English, also because their nature is unclear prior to search. Second, as the shocks are estimated from the dynamic factor model, some may not correspond to real uncertainty shocks but just to periods where the data did not match the assumed data generating process. Both lead to the fact that I could only identify few "real" policy uncertainty shocks for the European countries. It is beyond the scope of this paper to identify further shocks, and hence evidence provided by using these shocks should be considered anecdotal at best. Nonetheless, it is an interesting task for future research to construct narrative evidence for exogenous policy-shocks.

To avoid attributing too many uncertainty effects shocks that were largely economic in nature, shocks related to the Russian crisis (September 1998), the collapse of the Lehman Brothers (September 2008) and the worsening of the Euro-crisis (late 2011 and early 2012) are not regarded as exogenous EPU shocks due to their potential direct economic impacts. Shocks that cannot be related to a specific event are disregarded as no arguments about their exogeneity can be made. Last, shocks that arguably do not originate in the country of interest but show as a spike in idiosyncratic uncertainty are also discarded to avoid attributing international shocks to the wrong country. This classification is discussed in further detail in Appendix B.2.

This results in a dummy series per country with the following non-zero elements:

- the US: 2000 elections (2000M11), 9/11 (2001M09), Run-up to the midterm elections 2010 (2010M07 and 2010M09), Debt ceiling debate (2011M07 and 2011M08), the fiscal cliff (2012M12), 2013 government shut-down (2013M09 and 2013M10).
- France: 2004 regional elections (2004M04), Sarkozy becomes president of UMP (2004M11), protests about planned pension reforms (2010M10), 2012 General elections (2012M04 and 2012M06)
- Germany: "Sparpaket debate" (1999M08), 2003 Regional elections (2003M02), 2005 General election (2005M09)
- Italy: Biagi reform(2001M11 and 2002M06), General election stalemate 2013 (2013M01, 2013M02, and 2013M03)
- the UK: Crisis of the Northern Rock bank (2007M09), Scottish referendum to leave the UK (2014M08 and 2014M09), General election 2015 (2015M04)

This approach is clearly very subjective in classifying events as exogenous or not, hence any evidence resulting from this classification should be considered anecdotal, and serves only as a robustness check of previously found results[8]. Further, using only between 3 (Germany) and 9 (US) dummies as an instrument to identify the effects of policy uncertainty is not optimal, given

[7] Sources are cited in Appendix B.2 where I elaborate in more detail on the events on each date.

[8] I also considered using the full dummy series, where no dummies are excluded, as an instrument for uncertainty shocks. For the US and Germany, this brings results that are very similar to those found when the idiosyncratic error-term is used as an instrument. For Italy and the UK, the results are more similar to the

that there is very little variation to control for other differences, especially as some countries have dummies that all lie in a very narrow time-frame. Nevertheless, this approach is very similar to that of Ramey (2011), who used 4 war spending shocks to model exogenous government spending shocks. Additionally, using such a series of dummies as an instrument may be problematic due to weak-instrument bias if the dummy series is not sufficiently relevant in predicting shocks in uncertainty. However, it is important to note that neither instrument is weak: Stock et al. (2002) require a first stage F-statistic of above 9 to reject the null hypothesis of weak instruments, which all considered series, both the dummy variables and the idiosyncratic error term, fulfil.

5 Modelling the dynamic relationship between uncertainty and economic variables

The basic framework in which this paper considers the dynamic relationship between economic policy uncertainty and macroeconomic variables is that of structural vector autoregressive (SVAR) models. That is, the following class of models is considered:

$$\boldsymbol{B_0 Y_t} = \boldsymbol{B}(L)\boldsymbol{Y}_{t-1} + \epsilon_t,\ \epsilon_t \sim \boldsymbol{\mathcal{N}}(0,\, \boldsymbol{\Sigma}_\epsilon),\ \text{for } t \in \{1, \ldots, T\} \tag{4}$$

where the $k \times 1$ vector $\mathbf{Y_t}$ denotes a vector of (macroeconomic) variables as observed at time t, and $\boldsymbol{\Sigma}_\epsilon$ is a diagonal variance-covariance matrix, implying zero correlation between the structural shocks $\boldsymbol{\epsilon_t}$(Lütkepohl, 2005). The $k \times k$ matrix $\boldsymbol{B}_0$ on the left-hand side characterizes the contemporaneous effects that variables have on each other, and identification of this matrix can be interpreted as a simultaneous equation problem. The lag-polynomial $\boldsymbol{B}(L)$ on the right-hand side characterizes the dynamic relationships between variables. Within this paper, these two parts of the model are essentially regarded as two separate problems. The dynamic problem on the right-hand side is relatively simple to model by considering the reduced form of (4): $Y_t = \boldsymbol{A}(L)\boldsymbol{Y}_{t-1} + u_t$, where $\boldsymbol{A}(L) = \boldsymbol{B_0}^{-1}\boldsymbol{B}(L)$ and $u_t = \boldsymbol{B_0}^{-1}\epsilon_t$. The dynamic specification of lag-polynomial $\boldsymbol{A}(L)$ will be discussed in detail in section 5.1. The contemporaneous effects on the left-hand side of (4), however, are much more difficult to determine from the reduced form equation. As discussed in the previous section, this is due to identification issues that plague any form of simultaneous equation model. For identification of $\boldsymbol{B_0}^{-1}$, the exclusion restrictions and external instruments discussed in the previous section are needed. How they are used in this framework will be discussed in further detail in section 5.2. When both parts of the equation are identified, the dynamic effect of shocks can be traced through the system using impulse response analysis. This will be discussed in detail in section 5.3.

5.1 Dynamic model specification

Baker et al. (2016) model the dynamic relationship between economic policy uncertainty and macroeconomic variables in a simple vector autoregressive (VAR) model of the form

$$\mathbf{Y_t} = c + A_1\mathbf{Y_{t-1}} + \ldots + A_p\mathbf{Y_{t-p}} + \mathbf{u_t},\ \mathbf{u_t} \sim \boldsymbol{\mathcal{N}}(0,\, \boldsymbol{\Sigma}_u),\ \text{for } t \in \{1, \ldots, T\} \tag{5}$$

results found when using the dummy series constructed in this section. For France, results resemble those using the Cholesky decomposition when EPU series first. These results are not presented in this paper as they offer very few insights in addition to the presented identification strategies, but are available upon request.

where the $k \times 1$ vector $\mathbf{Y_t}$ denotes a vector of (macroeconomic) variables as observed at time t, c is a vector of constants, A_j is a $k \times k$ coefficient matrix for the j^{th} lag of $\boldsymbol{Y_t}$, for $j = 1, \ldots, p$ and lag-order p, and $\mathbf{u_t}$ is the normally distributed error term. To allow for potential distinct dynamics throughout the business cycle, this paper extends this to a smooth transition vector autoregressive model (STVAR) similar to Caggiano et al. (2017a), with the following specification

$$\mathbf{Y_t} = F(Z_{t-1})(c_E + \textstyle\sum_{i=1}^{p} A_{i,E}\mathbf{Y_{t-i}}) + (1 - F(Z_{t-1}))(c_R + \textstyle\sum_{i=1}^{p} A_{i,R}\mathbf{Y_{t-i}}) + \mathbf{u_t},\ \mathbf{u_t} \sim \boldsymbol{\mathcal{N}}(0,\, \boldsymbol{\Sigma}_u) \tag{6}$$

$$\text{with } F(Z_t) = \frac{\exp(\gamma(Z_t - c))}{1 + \exp(\gamma(Z_t - c))}, \text{ where } \gamma > 0, \text{ for } t \in \{1, \ldots, T\}. \tag{7}$$

Specification (6) allows for two different sets of autoregressive parameters, where subscript R denotes recession-parameters and E indicates expansions, weighted by the realization of a logistic transition function $F(Z_{t-1})$. Here, $F(Z_{t-1})$ allows for each observation to be in a recession (if $F(Z_{t-1})$ approaches 0), in an expansion (if $F(Z_{t-1})$ approaches 1) or transitioning from one state to another (for intermediate values of $F(Z_{t-1})$). To model the state of the economy, this paper follows Caggiano et al. (2017a) in constructing a transition-variable Z_t^6 as a moving average of the growth rate of industrial production over the last 6 periods. Using a transformation of IP growth as the transition variable has the advantage that, as IP is already explicitly modeled as part of vector $\boldsymbol{Y}_t$, the model allows for a shock in EPU to cause a change in the state of the economy. In this paper, the lag-order p is selected based on the Akaike information criterion (AIC) for the linear versions of the model, prior to estimation of the STVAR model. This approach is adapted from Caggiano et al. (2017c).

To test for non-linearity and hence applicability of model (6), one has to take into account that under the null hypothesis of linearity, the parameters γ and c in the transition function are unidentified nuisance parameters. Therefore, the linear VAR and the STVAR cannot be tested against each other using a simple likelihood-ratio or F-test. Instead, the test proposed by Terasvirta and Yang (2014), which uses a Taylor expansion of the transition function to circumvent identification issues, is applied in this paper. For a brief description of the test procedure, see appendix C.3.1.

For estimation of parameters in a standard VAR-model, an ordinary least squares (OLS) estimator can be used, whereas estimation of the STVAR model requires a procedure suitable for non-linear functions. Note that if γ and c were known, regime-dependent coefficients could be easily estimated using an OLS estimator (Hubrich and Teräsvirta, 2013), and hence estimation can be done by iteratively optimising over the parameters in the transition function and the lag-polynomials. This reduces to an iterative non-linear least squares (NLS) approach in

$$\theta_{NLS} = argmin_\theta \sum_{t=1}^{T} (\boldsymbol{y}_t - \boldsymbol{B}\boldsymbol{X}_t(\gamma, c))'\Sigma^{-1}(\boldsymbol{y}_t - \boldsymbol{B}\boldsymbol{X}_t(\gamma, c)) \tag{8}$$

where $\boldsymbol{X}_t(\gamma, c) = [\boldsymbol{Y}'_{t-1}F(Z_{t-1}), \ldots, \boldsymbol{Y}'_{t-p}F(Z_{t-1}), \boldsymbol{Y}'_{t-1}(1 - F(Z_{t-1})), \ldots, \boldsymbol{Y}'_{t-p}(1 - F(Z_{t-1}))]'$, $\boldsymbol{B} = [c_E, A_{1,E}, \ldots, A_{p,E}, c_R, A_{1,R}, \ldots, A_{p,R}]$, θ summarizes all the model parameters, and $\Sigma = I$.

Starting values for γ and c should be obtained from a grid-search (Hubrich and Teräsvirta, 2013).

Due to the non-linearity of the STVAR-model, however, asymptotic standard errors for functions of the parameter estimates have no standard approximation. In this paper, impulse response functions are of main interest, and therefore an alternative strategy to compute parameter estimates and functions of parameter estimates is needed. Hence, following the approaches of Auerbach and Gorodnichenko (2012) and Gefang and Strachan (2010), parameter estimates are obtained using Bayesian simulation methods. Gefang and Strachan (2010) derive the posterior distributions of the different model parameters in an STVAR-model. Given γ and c, the conditional posterior distribution of $vec(\boldsymbol{B})$ is normal, while the conditional posterior distributions of γ and c have non-standard forms. Therefore, this paper considers γ and c fixed parameters in the simulation. This is in line with the approach of, for example, Auerbach and Gorodnichenko (2012) and Caggiano et al. (2014). Further, this also allows to "force" moderate values of γ and c. For large γ, there is a sharp distinction between recession and expansion regimes, and the model essentially becomes a threshold model. As, however, the samples contain only two or three NBER recessions, depending on the country-specific availability of EPU data, and the recessionary lag-polynomial contains $k \times (k \times p + 1)$ parameters, this results in very badly identified parameter estimates. Therefore, estimates of γ and c will be obtained by optimizing (8) where γ is restricted to have a maximum value of 2. Here, 2 is chosen as an upper bound as values larger in magnitude transform the transition function to a threshold model. This is effect is illustrated in Figure 3 in section 6, which shows the transition function for restricted and unrestricted estimates of γ and c. The estimates of γ and c obtained in the restricted iterative NLS-estimation are then treated as fixed when estimates of $\boldsymbol{B}$ are generated in a Gibbs-sampling procedure.

Under the assumption of fixed γ and c, model (6) reduces to a VAR model, for which Bayesian estimation methods have been widely investigated. For a comprehensive discussion of these methods for VARs, refer to Lütkepohl (2005). In the following discussion, $\boldsymbol{B}$ is defined as in equation (8), and $\boldsymbol{X} = [\boldsymbol{X}_{p+1}(\gamma, c), \ldots, \boldsymbol{X}_T(\gamma, c)]$. The choice of prior distributions is crucial for parameter estimation and simulation. A diffuse prior for $vec(\boldsymbol{B})$ results in a normal posterior distribution with mean $vec(\hat{\boldsymbol{B}}_{OLS})$ and variance $\widehat{Var(\hat{\boldsymbol{B}})}_{OLS}$, which, due to the relatively short sample, results in very high parameter variance especially for the recessionary lag-polynomial. Therefore, this paper employs an adapted Minnesota prior for $vec(\boldsymbol{B})$ which is a normal distribution with prior mean equal to zero for all elements of $vec(\boldsymbol{B})$, and prior variance-covariance matrix $\boldsymbol{V}$ of parameters that is diagonal and shrinks the parameter estimates towards zero at different speeds. In this paper, matrix $\boldsymbol{V}$ has the following diagonal elements:

$$Var(a^s_{ij,l}) = \begin{cases} \frac{\pi_1}{l^2} \text{ if } i = j \\ \frac{\pi_2 \sigma_i^2}{l^2 \sigma_j^2} \text{ if } i \neq j \end{cases} \quad \text{and } Var(c_i^s) = \pi_3 \sigma_i^2 \tag{9}$$

where $a^s_{ij,l}$ refers to the j^{th} element in the i^{th} row of the matrix A^s_l, with s denoting the state of the economy (E or R) and l the lag. The parameters π_1, π_2 and π_3 are set to 0.05, 0.005 and 10^3, respectively, following the discussion in Kadiyala and Karlsson (1997). This prior variance specification reflects the prior belief that the coefficients of higher lags should be closer to zero, that other variables j affect variable i less than its own lag (as $\pi_1 > \pi_2$), and that the magnitude of effects are scaled by the difference in error-variances of the series. In a strict Bayesian approach, the σ_i would have to be modelled too. However, to reduce the difficulty of the problem, Lütkepohl (2005) and Kadiyala and Karlsson (1997) fix these parameters prior to estimation. In line with Lütkepohl (2005), this paper sets the σ_i as the square-root of the diagonal elements of $\frac{1}{T}(\boldsymbol{y} - \hat{\boldsymbol{B}}_{OLS}\boldsymbol{X})(\boldsymbol{y} - \hat{\boldsymbol{B}}_{OLS}\boldsymbol{X})'$. Hence, the prior distribution of $vec(\boldsymbol{B})$ is specified as: $vec(\boldsymbol{B}) \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{V})$. As $\boldsymbol{\Sigma_u}$ is unknown too, a standard diffuse prior $p(\boldsymbol{\Sigma_u}) \propto |\boldsymbol{\Sigma}_u|^{-(k+1)/2}$ is chosen. Then, the conditional posterior distributions can be shown to equal

$$vec(\boldsymbol{B})|\boldsymbol{\Sigma_u}, \gamma, c \sim N(\bar{b}, \bar{\boldsymbol{V}}) \text{ and } \boldsymbol{\Sigma_u}|\boldsymbol{B}, \gamma, c \sim IW(EE', T)$$

where $\bar{\boldsymbol{V}} = (\boldsymbol{V}^{-1} + (\boldsymbol{X}\boldsymbol{X'} \otimes \boldsymbol{\Sigma}_{\boldsymbol{u}}^{-1}))^{-1}$, $\bar{b} = \bar{\boldsymbol{V}}\boldsymbol{V}^{-1}vec(\hat{\boldsymbol{B}}_{OLS})$ and
$EE' = (\boldsymbol{y} - \boldsymbol{B}\boldsymbol{X})(\boldsymbol{y} - \boldsymbol{B}\boldsymbol{X})'$(Gefang and Strachan (2010), Lütkepohl (2005) and Sevinç and Ergün (2009)). Given these conditional posterior distributions, a simple Gibbs-sampler can be employed to obtain parameter estimates by iteratively drawing from the conditional distributions. In this paper, 10200 such draws are taken, of which the first 200 are discarded, in line with the burn-in period suggested by Kadiyala and Karlsson (1997) and Sevinç and Ergün (2009). These chains of parameter estimates will then be used to construct orthogonal shocks and impulse response functions, as will be discussed in Sections 5.2 and 5.3, respectively.

5.2 Construction of orthogonal shocks

As discussed above, models (5) and (6) both can be interpreted as the reduced form representation of a structural vector autoregression (SVAR). In general, the elements of reduced form error vector $\boldsymbol{u_t}$ are not uncorrelated, which means that shocks to a variable not only have dynamic effects on other variables, but could also contemporaneously affect them. In order to disentangle the effect of shocks to different variables in these model specifications, structural shocks ϵ_t need to be reconstructed. That is, one needs to construct matrix $\boldsymbol{H}$ such that

$$\boldsymbol{u_t} = \boldsymbol{H}\boldsymbol{\epsilon_t} \text{ where } \epsilon_{\mathbf{t}} \sim \boldsymbol{\mathcal{N}}(0, \boldsymbol{\Sigma}_\epsilon), \text{ for } t \in \{1, \ldots, T\} \tag{10}$$

and $\boldsymbol{\Sigma}_\epsilon$ is a diagonal matrix, implying zero correlation between the structural shocks $\boldsymbol{\epsilon_t}$.

As discussed in Section 4, Baker et al. (2016) use the lower-triangular Cholesky decomposition of $\boldsymbol{\Sigma_u}$ to model matrix $\boldsymbol{H}$. Mathematically this means they use $\boldsymbol{H} = \boldsymbol{P}$, where $\boldsymbol{P}$ is chosen such that $\boldsymbol{\Sigma_u} = \boldsymbol{P}\boldsymbol{P'}$, where they order US EPU before all other variables. To follow their approach, one identification strategy used in this paper therefore is to order EPU first in a Cholesky decomposition. Additionally, this paper also uses external instruments, variables not already included in the vector $\boldsymbol{Y_t}$, to identify (parts of) $\boldsymbol{H}$. The approach, as derived by Stock and Watson (2018), relies on the fact that (10) implies that

$$u_{i,t} = h_{i1}\epsilon_{1,t} + \ldots + h_{ik}\epsilon_{k,t} \text{ for } i \in \{1, \ldots, k\} \text{ and } t \in \{1, \ldots, T\}. \tag{11}$$

As estimates of the reduced form shocks, $\hat{u}_{i,t}$, can be obtained from the residuals of the STVAR models, identification of the j-th column of $\boldsymbol{H}$ can be achieved if a suitable exogenous instrument Z_t for $\epsilon_{j,t}$ is found. Stock and Watson (2018) argue that h_{ij} is identified up to scale by the IV-regression in which $\hat{u}_{it}$ is regressed on $\hat{u}_{jt}$ using exogenous instrument Z_t. After assuming the unit effect normalization, $H_{11} = 1$, the population estimator is given by $\hat{H}_{ij} = \frac{E(\hat{u}_{it}Z_t)}{E(\hat{u}_{jt}Z_t)} = \frac{\hat{\boldsymbol{u}}_i^T \boldsymbol{Z}}{\hat{\boldsymbol{u}}_j^T \boldsymbol{Z}}$. The country-specific idiosyncratic error-term and the dummy series constructed using the dynamic factor model in Section 4 will both be used as instrument Z_t. Note that the external instruments will be used only to identify structural shocks, and not be included in the STVAR themselves[9]. Using the exogenous component in the model directly would forbid to consider dynamic feedback effects of movements in the endogenous variables, and hence I consider it less preferable than the approach employed here. Further, this approach has the advantage that matrix $\boldsymbol{H}$ can, if necessary, be constructed using only a sub-sample, and hence external instruments for the shocks do not have to be available over the whole sample(Stock and Watson, 2018). In this paper, this is the case, as both instrument-series are only constructed for the time-span 1997M01 to 2015M12, which, for France, Germany and the US, is shorter than the sample considered for the estimation of dynamic effects.

If the external instruments are not truly exogenous with respect to the macroeconomic variables, then, similarly to a Cholesky decomposition with EPU ordered first, too much contemporaneous variation will be attributed to EPU shocks. In addition to using the dummy series of "exogenous events" to consider robustness of results, the EPU series will be ordered last in a Cholesky decomposition as an additional robustness test. This allows to investigate whether dynamic effects are entirely dependent on attribution of contemporaneous effects to EPU.

5.3 Impulse response analysis

After reconstruction of structural shocks, the proposed models can be used to investigate the dynamic effect of an exogenous shock to one variable on the other variables in the system, using impulse response function (IRF) analysis. In the simple VAR-model used by Baker et al. (2016), one can derive the impulse response function by using the moving average representation of equation (5) and $\boldsymbol{H}$(Lütkepohl, 2005).

Given the non-linearity of the STVAR-model, simple impulse-response analysis is no longer feasible as responses are dependent on the state of the economy and the history of shocks at any point in time. One approach would be to follow Auerbach and Gorodnichenko (2012) and Fontaine et al. (2017) and assume for impulse response analysis that the state of the economy remains constant. Then, it is possible to consider only the regime-specific lag-polynomial, whose IRF has the standard closed-form representation.

Yet, this ignores the possible effect a structural shock could have on the state of the economy. Therefore, this paper considers generalised impulse response functions (GIRFs) for the STVAR, which are based on differences in expectations conditional on history (Koop et al., 1996), and have to be simulated in line with an approach described by Hubrich and Teräsvirta (2013). The

[9] In this paper, I use the external instruments only for identification in the STVAR model, not in the linear VAR. The usage of the linear VAR serves only as a replication of the results of Baker et al. (2016), who use Cholesky decompositions. The extension of identification methods is considered in the less constrained STVAR framework.

generalised impulse response function is a random variable, computed as the expected value of the change in $\boldsymbol{y}_{t+h}$ as a result of a fixed shock δ to variable i at time t, given a specific history $\Omega_{t-1} = \{\boldsymbol{y}_{t-1}, \ldots, \boldsymbol{y}_{t-p-1}\}$ and the parameter estimates of the STVAR model, θ. That is,

$$GIRF(h, \epsilon_t, \Omega_{t-1}, \theta) = E(\boldsymbol{y}_{t+h}|\epsilon_t^{\delta}, \Omega_{t-1}, \theta) - E(y_{t+h}|\Omega_{t-1}, \theta), \text{ for } h \in \{0, 1, \ldots\} \tag{12}$$

While standard IRF estimates impose that all future shocks are zero, the expected value in the definition of the GIRF indicates that future shocks are incorporated by simulation, but averaged out later. Further, in a GIRF observations are not restricted to lie fully in a recession or expansion (which would mean $F(Z_{t-1}) = 0$ or $F(Z_{t-1}) = 1$), and hence the GIRFs can actually be a mixture of the two regime-specific IRFs considered by Auerbach and Gorodnichenko (2012) and Fontaine et al. (2017). As the GIRF approach offers a more accurate and less restrictive representation of the propagation of shocks through a non-linear system, this paper will focus on GIRF estimates. A comparison of the two approaches to impulse response analysis is shown in Apendix D.2.

To compute GIRF estimates, simulation methods that sample from the model residuals $\hat{\boldsymbol{u}}_t$ are used in an approach adapted from Hubrich and Teräsvirta (2013). To compute the recession-specific GIRFs, starting time t and corresponding history Ω_{t-1} is drawn from all observations for which it holds that $F(Z_{t-1}) \leq 0.5$. Then, a sequence of h elements is drawn with replacement from the set of all reduced form residuals $\hat{\boldsymbol{u}}_t$, and a second sequence is formed by replacing the first shock by $\boldsymbol{u}_t^{\boldsymbol{\delta},*} = \boldsymbol{u}_t^* + H_{.i}\delta$, where i is the variable of interest. Throughout, δ is chosen to be a shock of the size of one standard deviation of the variable of interest, in line with a majority of literature in the field (for example, Fontaine et al. (2017), Caggiano et al. (2014), and Caggiano et al. (2017a)). Both sequences of errors are then used to generate two sequences $\boldsymbol{y}_t^*, \ldots, \boldsymbol{y}_{t+h}^*$ and $\boldsymbol{y}_t^{\boldsymbol{\delta},*}, \ldots, \boldsymbol{y}_{t+h}^{\boldsymbol{\delta},*}$ by using the estimated STVAR model in conjunction with history Ω_{t-1}. The difference of the two sequences captures the generalised impulse response, and to obtain an expected value, this procedure is repeated for 200 random draws with replacement of starting times and residuals.[10] For expansions, estimation of the GIRF proceeds analogously, except that t and corresponding Ω_{t-1} are chosen from the set of observations for which $F(Z_{t-1}) > 0.5$.

Some literature suggesting GIRFs assumes in construction of their GIRFs that all estimates of parameters in the STVAR, θ, are fixed(for example, Kilian and Vigfusson (2011) and Hubrich and Teräsvirta (2013)). To avoid this strict assumption, the approach of Gefang and Strachan (2010) who simulate parameters from their posterior distribution, is adapted here.[11] This

[10]The procedure used here deviates from suggestions of Hubrich and Teräsvirta (2013) because they use Cholesky decompositions for identification of orthogonal shocks. More specifically, the procedure suggested by Hubrich and Teräsvirta (2013) differs from the one used in this paper in two points: first, it is suggested to sample from the orthogonalised model residuals $\hat{\boldsymbol{\epsilon}}_t$, yet this is not possible in the given context as the external instrument approach only allows for reconstruction of the i^{th} column of matrix $\boldsymbol{H}$, and not the full matrix $\boldsymbol{H}$, which would be necessary to construct series of orthogonalised residuals. Second, it is suggested to replace the i^{th} element of the first structural shock with δ, instead of adding $H_{.i}\delta$ to the first reduced-form shock – yet this is also not possible here as structural shocks cannot be reconstructed fully.

[11]Note that even these confidence intervals do not capture all sources of parameter uncertainty: on the one hand, parameter estimates γ and c are treated as fixed as previously discussed. On the other hand, $H_{.1}$ is effectively treated as fixed given the error terms corresponding to parameter draw θ_j. This is similar to the approaches of, for example Auerbach and Gorodnichenko (2012) and Gefang and Strachan (2010), in that these treat the Cholesky decomposition $\boldsymbol{P}$ as the true value of the contemporaneous relations. Therefore, although the

means that (12) is simulated for multiple draws of θ_j: more specifically, $j = 1000$ random draws from the simulated chain of STVAR-parameter estimates are taken, for each draw $H^j_{.i}$ is computed, and the GIRF is simulated as the mean of 200 draws of histories and residuals. Then, the median GIRF of the 1000 repetitions is taken as the final estimate[12], and the displayed confidence bands correspond to the percentiles of the simulated posterior distribution of GIRFs. The exact estimation algorithm of the GIRFs, summarizing the discussion in Sections 5.1, 5.2 and 5.3, can be found in Appendix D.1.

6 Results

This section is structured as follows: First, the baseline results of Baker et al. (2016) are replicated and discussed. Second, the baseline analysis of Baker et al. (2016) is repeated using growth rates instead of level series, and extended to allow for different impulse responses during expansions and recessions, and different identification strategies. Third, European EPU series and export growth rates are included in the extended analysis. Fourth, the differences between the country-level results is discussed.

6.1 Replication and discussion of Baker et al. (2016)'s results

As this paper takes as a point of departure the work of Baker et al. (2016) on EPU indices, I begin by discussing their findings with regards to the dynamic relationship of US EPU and the levels of industrial production and employment. Baker et al. (2016)'s baseline specification uses a VAR(3) to model the vector of variables $Y_t = [EPU_t^{US}, log(SP500_t), FFR_t, log(Empl_t), log(IP_t)]$ over the period 1985M01 to 2014M10. A replication of their exact baseline result and a replication of their baseline results using the data of this paper can be found in Figure A.1 in Appendix A. While they find a significantly negative effect of a 97 point EPU increase, which corresponds to the average increase in EPU between 2005-06 and 2011, of maximally 0.35% on employment and 1.1% on industrial production, these results should be interpreted with caution. The lag-polynomial of their baseline VAR has four eigenvalues with modulus very close to 1 (0.995, 0.967, 0.968 and 0.968) which can be taken as tentative evidence for instability of the system.

Before considering growth rates of employment and industrial production, which will be the approach of the remaining sections of this paper, it is hence of interest to consider whether the non-stationary level-series included in the VAR have any common stochastic trends, that is, whether they are cointegrated[13]. Therefore, I test their baseline data for the presence cointegration using the Johansen (1991) trace test and find significant evidence that the system is cointegrated of order three[14]. While the OLS-parameter estimates presented by Baker et al.

confidence intervals used in this paper aim to capture large parts of parameter uncertainty, they still have to be seen as upper bounds on the confidence.

[12] The median is used instead of the mean due to the lower sensitivity to large outliers. This is in line with Gefang and Strachan (2010).

[13] I would like to thank my thesis supervisor, Professor dr. R.L. Lumsdaine, who suggested this investigation into the presence of cointegration, and provided me with relevant references and insights into why this may be interesting in the given context.

[14] As the cointegration analysis presented here only serves the purpose of illustrating that considering growth rates may mask some long-term effects of EPU, I will not discuss methodological details relating to cointegration in this paper. For a discussion of cointegration, its effects and estimation methods for cointegrated time-series, refer to Lütkepohl (2005).

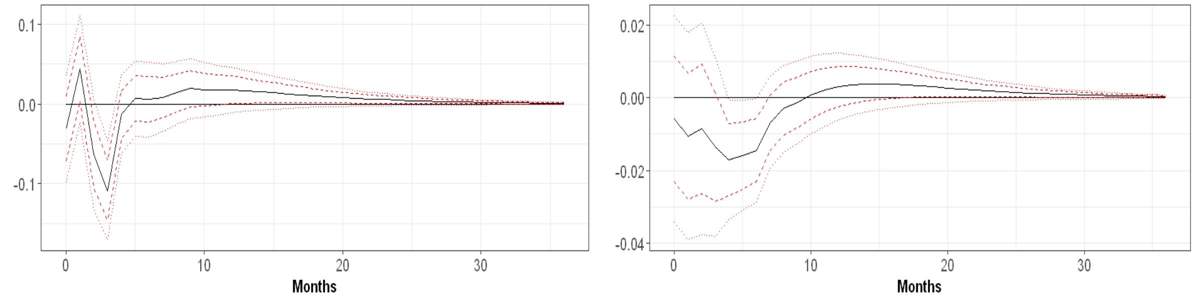
(2016) remain consistent even if the system is cointegrated (Sims et al., 1990), the variance-covariance matrix of the parameter-estimates is singular. Therefore, the asymptotic distribution of parameter-estimates and of the impulse response function is non-standard (Sims et al., 1990). To investigate the impact of these cointegration relations on the finite-sample results presented by Baker et al. (2016), a vector-error correction model (VECM) with three cointegration relations and lag-order three is estimated, and the corresponding impulse response functions are presented in Appendix A. The point estimates of the responses in both employment and IP in the early months do not change substantially, and remain significant. In the long-run, however, the IRFs do not converge back to zero. The response in IP converges towards a negative effect of 1% in the long-run, which, however, is not significantly different from zero. The response in employment converges towards a persistent negative effect of 0.45%, which is significantly different from zero. Thus, some evidence is provided that a large increase in US EPU may have some persistent effects on US macroeconomic level series.

6.2 Effects of domestic economic policy uncertainty shocks on US economic growth

As discussed in Section 3, I ensure that all my input series are weakly stationary by using the first differences of log-transformed employment, log-transformed industrial production, FFR and the log-transformed S&P500 index in further analysis to simplify the (non-linear) analysis. On the one hand, one could argue that as the level series are cointegrated, this approach distorts parts of the relationship between the original variables, as the cointegration relationships are lost in differencing. On the other hand, this approach has the advantage that the log-transformed series, employment and IP in particular, are now included in their growth rates – which, as previously discussed, are interesting to investigate by their own merit. Thus, this paper is effectively investigating the effect of EPU on economic growth instead of level series for the remainder of this paper.

I begin the investigation into the effects of EPU on economic growth by replicating the baseline analysis of Baker et al. (2016) for the adjusted vector of variables $Y_t = [EPU_t^{US}, \Delta log(SP500_t), \Delta FFR, \Delta log(Empl_t), \Delta log(IP_t)]$. Unless specified otherwise, this is also the ordering of variables whenever a Cholesky decomposition is used in this section. The AIC suggests 3 lags for this adjusted specification, thus a VAR(3) is estimated and no further evidence for instability of the system is found. Figure 2 presents impulse response functions of IP and employment growth rates. As previously discussed, instead of using the 97-point EPU increase as a shock like Baker et al. (2016), I consider one-standard deviation shocks for the remainder of this paper. This is both the standard in literature, and simplifies the comparison to shocks in international EPU series that will be considered later in this paper. Further, it seems to be standard in related literature to base conclusions on 68% confidence intervals[15] instead of more common 90% or 95% confidence intervals. Therefore, throughout this paper the narrow 68% confidence intervals will be presented alongside wider 90% intervals, to be able to compare findings with published literature.

[15] For example, Caggiano et al. (2017a) base their conclusion that US EPU shocks affect employment and IP significantly during recessions on such intervals, and Fontaine et al. (2017) use them for the conclusion that Chinese EPU has significant impacts on US macroeconomic outcomes during recessions.



(a) IP growth rate (in percent)

(b) Employment growth rate (in percent)

Figure 2: Impulse responses to a one-standard deviation shock to US EPU
This graph shows the responses of the growth rates in IP and Employment to a one-standard deviation shock to US EPU (40.18 points). Growth rates were multiplied by 100. Parameters were estimated in a VAR(3) over the sample January 1987 to December 2015. Orthogonal shocks were reconstructed using a Cholesky decomposition on basis of the ordering $Y_t = [EPU_t^{US}, \Delta log(SP500_t), \Delta FFR, \Delta log(Empl_t), \Delta log(IP_t)]$. Red dashed lines represent asymptotic 68% confidence intervals, red dotted lines indicate 90% confidence intervals.

When considering growth rates, there is some significant evidence that employment is impacted by a shock in EPU. After 4 months, the response in employment growth shows a negative effect of 0.02%, which is different from zero at a 90% confidence-level. To put this number into perspective, it corresponds to a drop of almost a quarter of the mean employment growth rate of the entire sample, which is 0.09%. The growth rate of industrial production is significantly impacted at a 90% confidence-level and falls by 0.11% after 3 months, corresponding to a reduction of two thirds of the mean IP-growth of 0.16%.

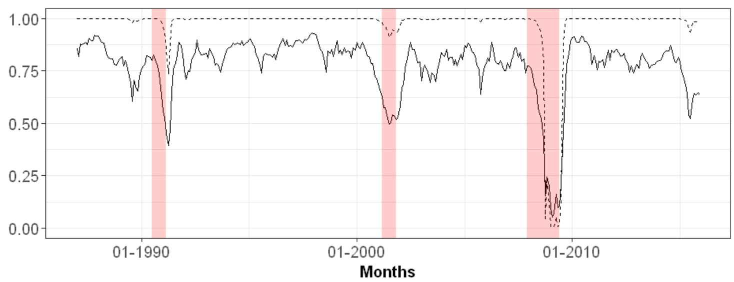


Figure 3: Evolution of unrestricted (dotted line) and restricted (solid line) transition function
This figure shows the transition function as defined in (7) with transition variable the 6-month growth rate in IP for two combinations of γ and c. The solid line represents the pair ($\gamma = 2$, $c = -0.49$), the estimate resulting from the restriction that $\gamma \leq 2$, and the dashed line represents the pair ($\gamma = 6.37$, $c = -0.67$), the estimate resulting from unrestricted estimation. The red shaded areas represent NBER recessions.

Next, this adjusted baseline specification is tested for the presence of non-linearity using the Terasvirta and Yang (2014) test to establish applicability of the STVAR model. Test results are presented in Appendix C.2, and linearity is rejected at 1% significance-level for all tested orders of the Taylor expansion. Figure 3 displays the transition function estimated through the NLS procedure discussed in section 5.1. The upper bound on γ was set as 2, and the final estimate takes on this value. This is also the case for most transition functions of the models containing European EPU indices discussed later. When unrestricted estimation is performed, the resulting γ has value 6.37. As can be inferred from Figure 3, this creates a transition function with a sharp drop only in the most recent recession. Hence, a threshold model may have described the data better, but would restrict the observations available to estimate the recessionary parameters even further. Therefore, as discussed in Section 5.1, the restriction that $\gamma \leq 2$ is enforced throughout the paper.

Estimates of the STVAR model are then generated to investigate the macroeconomic effects of US EPU during recessions and expansions by using generalised impulse response functions with the different identification schemes. Figure E.1 in Appendix E presents GIRF estimates for recessions and expansions using Cholesky decompositions and external instruments. Figure 4 presents the GIRFs for recessions for illustrative purposes.

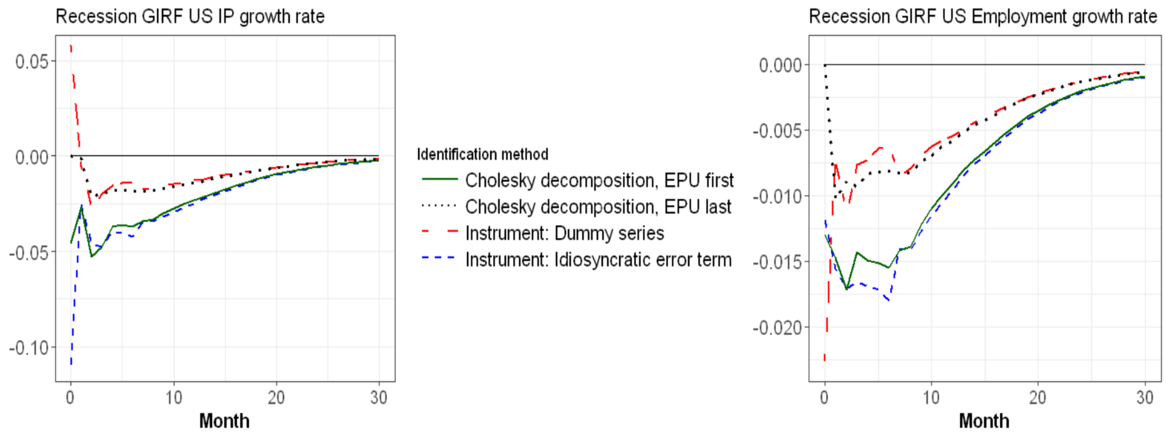


Figure 4: GIRFs of IP and employment growth to a one-standard deviation shock US EPU during recessions

This graph shows the responses during recessions of the growth rate in IP and Employment to a one-standard deviation shock to US EPU (40.18 points) using different identification methods of orthogonal shocks. Parameters of the STVAR-model were estimated over the sample January 1987 to December 2015. Confidence intervals are omitted for readability.

The displayed recession GIRFs indicate that EPU shocks indeed have negative effects on the growth rates of IP and employment. As expected, the results using the idiosyncratic error term as an external instrument look very similar to the Cholesky decomposition ordering US EPU first. Only the instantaneous response of the IP growth rate to a shock in EPU is substantially larger when using the external instrument, and the point estimate lies at around -0.1% instead of -0.05%. This could be due to the fact that through estimation of the dynamic factor model, some noise is removed from the EPU shocks. For both identification strategies, the dynamic response in the IP growth rate is a reduction of 0.04% to 0.05% during the first three months, which is just significantly different from zero at a 90% confidence-level. The impulse response function then converges back to zero within two years. The employment growth rate drops by 0.015% after 3 months, which is also significantly below zero at a 90% confidence-level.

To test whether these economic effects are to a large extent driven by (wrongly) attributing instantaneous variation in economic variables to uncertainty, consider the results using a Cholesky decomposition with EPU ordered last, and the results using the dummy series for identification. Both methods result in point estimates that indicate negative impulse responses that are of roughly half the magnitude as those discussed in the previous paragraph. Further, the response in employment growth remains different from zero only at a 68% confidence-level during both recessions and expansions, while the response in IP growth is different from zero at a 68%

confidence-level only during expansions. These findings indicate that attributing all contemporaneous variation in macroeconomic variables to EPU shocks may indeed have inflated the magnitude and significance of uncertainty effects if some shocks, such as the Lehman Brothers collapse in 2008, had direct economic effects independent of their uncertainty effect.

The GIRFs for expansions presented in Figure E.1 contain very similar results as those for recessions. While there is almost no difference in point estimates between recession and expansion GIRFs for IP growth, the magnitude of point estimates of responses of employment growth in the first months of expansions is slightly smaller and confidence intervals are more narrow than during recessions. For both variables in both regimes, the point estimates of effects are of smaller magnitude than those previously presented for the linear model. One possible explanation for this is that the chosen prior for the non-linear model has a high effect on the parameters given the small sample size, shrinking all estimates towards zero by construction, and the linear VAR results were not restricted in such a way (as they were estimated by simple OLS)[16].

The direction of the effects presented above is in line with Caggiano et al. (2017a)'s findings, however, they find substantially larger drops in the IP growth rate during recessions. This could stem from two sources: First, they have a larger sample at their disposal, starting in 1954, which includes more NBER recessions and hence helps to better distinguish recessionary and expansionary periods. Therefore, they also did not have to perform Bayesian estimation with shrinkage prior, but could obtain good estimates through the NLS procedure. Second, they replace the EPU series by a dummy series capturing only the largest spikes in EPU, hence, the magnitude of their EPU shocks is much larger.

6.3 Effects of European economic policy uncertainty shocks on US economic growth

In order to investigate whether EPU shocks originating in the European countries also have an effect on US macroeconomic variables, the vector $Y_t = [EPU_t^{US}, EPU_t^i, \Delta log(IP_t^i), \Delta log(SP500_t), \Delta FFR_t, \Delta log(Empl_t), \Delta log(IP_t)]$ is considered next, where i refers to one of the four considered European countries. The AIC suggests two or three lags for all country models, and for consistency, 3 lags are chosen for all countries. As can be inferred from the test results presented in Appendix C.2, the Terasvirta and Yang (2014) test rejects the null-hypothesis of linearity for all countries considered, therefore linear VAR estimates are not considered here. Appendix E, Figures E.2 to E.5, present the generalised impulse response functions of US EPU, the respective national IP growth rates, the US IP growth rate and the US employment growth rate to a one-standard deviation shock to EPU of the four considered countries for the four considered methods of identification and respective confidence intervals. To illustrate the most important features of these results, Figure 5 shows the GIRFs for a recession, where identification of orthogonal shocks is achieved by using the idiosyncratic error term from the dynamic factor model as an instrument.

[16]Nevertheless, the shrinkage prior is very useful. When re-estimating the results using a diffuse prior instead, the resulting impulse response functions are very badly identified, especially during recessions. This is not surprising given the arguments made in section 5.1: without proper prior, the posterior variance of the parameter estimates becomes very large as there are very few observations in recessions.

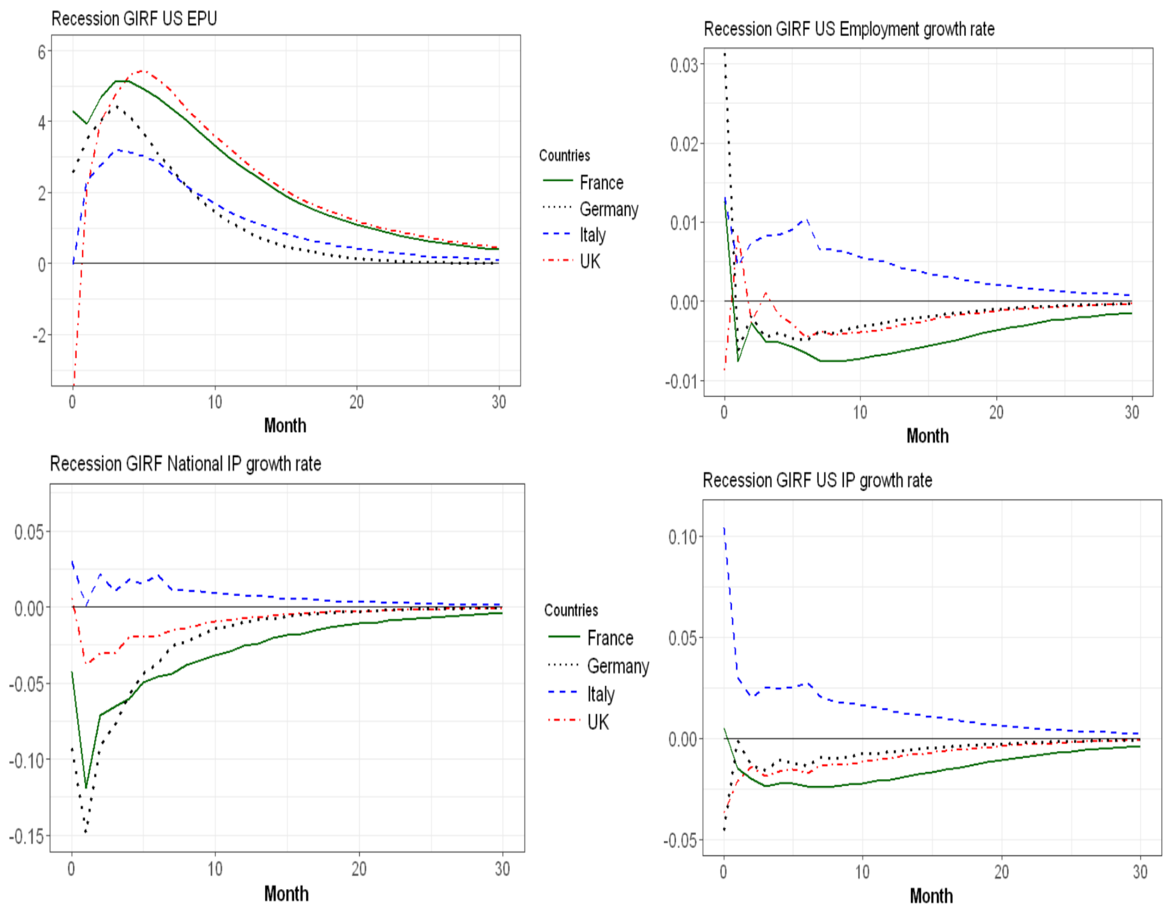


Figure 5: GIRFs for a one-standard deviation increase in European EPU during a recession, using the idiosyncratic error-term as an external instrument

This figure displays the generalised impulse response functions of US EPU, US employment growth, the national IP growth rate of the respective country, and the US IP growth rate to a one-standard deviation increase in EPU of the respective country. Identification of orthogonal shocks is achieved using the residual from the idiosyncratic update equation from the dynamic factor model as an instrument for uncertainty shocks. Confidence intervals are omitted for readability.

Although economic effects of European EPU shocks differ per country and will be discussed below, EPU spillover to the US is similar for all countries. Despite being different from zero at a confidence-level of at least 68% for all cases, the pure spillover of economic policy uncertainty is negligible. Point estimates using the different identification strategies range from maximum spillovers of 4 points (Italy) and 6 points (France) to 8 points (UK) and 9 points (Germany). Given that the EPU index for the US has a 40 point standard deviation over the considered sample, these effects are rather small and can be considered economically irrelevant despite their statistical significance. This also indicates no empirical support for an uncertainty spillover channel causing macroeconomic effects, which is in line with the findings of Klößner and Sekkel (2014) that the US tends to "export", and not "import" economic policy uncertainty. Therefore, it is of interest to more closely examine the evidence relating to economic channels of international uncertainty effects.

There is significant evidence that a shock to French EPU affects French IP growth, regardless of the used identification strategy. The maximum estimated drop in national IP growth is at least

0.1% for all used identification strategies. This is almost twice the negative effect a shock to US EPU has on US IP growth – however, given that there are no additional French control variables, this is only tentative evidence for domestic effects in France. There is some weak evidence that increased French EPU also has negative effects on US employment and IP growth. The point estimate of the effect during the first year lies at a negative effect of 0.005% on employment growth, and of -0.015 to -0.02% on IP growth, and the magnitudes of these effects are virtually the same during recessions and expansions. These point estimates amount to roughly half of the effect of a one-standard deviation shock to US EPU. Evidence on statistical significance of these estimates is mixed: when using the Cholesky decomposition with French EPU ordered first, only the response during recessions is just significantly different from zero at a 68% confidence-level starting three months after the EPU shock. When using external instruments, only the response during expansions is just different from zero at 68% confidence-level. The magnitude of these effects is also robust to ordering French EPU last in the Cholesky decomposition, although only the negative responses during recessions are significant at a 68%-level. Hence, the French results bring some weak evidence for the existence of an economic spillover channel.

Regardless of the used identification strategy, there is significant evidence (at least at a 68% confidence-level) that the German industrial production growth rate also reacts negatively to a shock in German EPU, with negative responses of between 0.1% and 0.25% one month after the shock. Further, this reaction is more pronounced and more persistent during US recessions than during US expansions. There is little evidence that a German EPU shock has an effect on US economic growth. Although point estimates of responses are negative when using the idiosyncratic error term as an instrument or the Cholesky decomposition with the EPU series ordered first for identification, they are not significantly different from zero. Identification using the dummy series does result in significantly negative effects on both US growth series, however, as the German dummy series contains only three non-zero elements, this cannot be considered reliable evidence. This is confirmed by the observation that when ordering the EPU series last in a Cholesky decomposition, even the point estimates of the reaction in the US growth series are zero. This shows that any dynamic effects of German EPU on the US growth series depend entirely on the instantaneous reaction of those series.

For all identification strategies used, there is no significant evidence that a shock to UK EPU has any significant impact on macroeconomic outcomes, both nationally and internationally. Unlike the evidence from Germany and France, there is no evidence that a UK EPU shock has any effect even domestically, hence it is not surprising that there is no spillover to the US[17].

Last, Italian IP growth also shows no significant reaction to an increase in Italian EPU. It is therefore surprising that the US macroeconomic variables show a significantly positive reaction to an Italian EPU shock, when using the different instruments and Cholesky decompositions ordering the EPU series first. This effect disappears when ordering Italian EPU last in a Cholesky decomposition. The observed positive effect may hence have been caused by episodes during

[17] To consider whether inclusion of Brexit changes these results, I re-estimated the STVAR for the UK using all data up to December 2017 and computed GIRFs using both types of Cholesky decomposition and a shock of 371 points, corresponding to the increase in UK EPU from May to June 2016. Nevertheless, the impulse response functions continue to indicate no significant economic effects. These results are available upon request.

which heightened Italian economic policy uncertainty coincided with better than expected economic performance of the US.

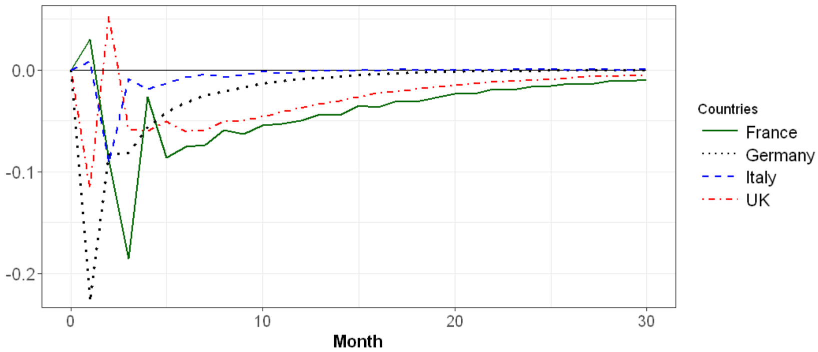


Figure 6: GIRFs of US exports to four European countries to a one-standard deviation shock to corresponding European EPU during a recession

This figure displays the generalised impulse response functions of the growth rate of US exports to a one-standard deviation shock to EPU of the respective country. Identification of orthogonal shocks is achieved using a Cholesky decomposition on basis of the ordering in $Y_t = [\Delta log(IP_t^i), \Delta log(exp_t^i), \Delta log(SP500_t), \Delta FFR, \Delta log(Empl_t), \Delta log(IP_t), EPU_t^{US}, EPU_t^i]$. Confidence intervals are omitted for readability.

To further investigate economic channels of uncertainty spillovers, the growth rate of US exports to the respective countries is included into the vector of variables, and ordered after the domestic IP growth rate of the country of interest. Estimates of the generalised impulse response functions, where identification is achieved by ordering the EPU series last in a Cholesky decomposition[18], are presented in appendix E, Figure E.6, and summarized in Figure 6 for recessions, as there are very few differences compared to the expansion estimates. Given the country-specific results discussed above, it is not surprising that only US exports to France are significantly impacted by a French EPU shock – and even these results are only just different from zero at a 68% significance level. In the French case, the significant estimated response to a standard deviation increase in French EPU is a 0.09% drop in the export growth rate after 5 months, which is declining to 0.05% within the first year. This constitutes some weak evidence indicating that French import demand for US goods may indeed decline in response to a French EPU shock. The point estimates for Germany and the UK seem similar, yet are not significantly different from zero even at a 68% confidence-level and, in the case of Germany, decline to zero faster. The point estimates of the growth rate of US exports to Italy show a reaction of much smaller magnitude and are also highly insignificant.

6.4 Discussion of country-level results

There could be multiple reasons for the differences in country-level results. First, the differences in results could reflect that economic agents in the different countries react differently to heightened economic policy uncertainty, for example due to differences in culture, history or legal provisions. In Italy, for example, policy uncertainty may be much more common than in the other countries: Italy has had 66 governments since the second world war (Henley, 2018) and

[18]This Cholesky decomposition is chosen for illustrative purposes here as it provides the most conservative estimates of impulse responses, in the sense that uncertainty shocks are not assumed to be exogenous to any other variables. Results using the other three methods of identification are available upon request.

is subject to a constant threat of political collapse (Stratfor, 2013). Therefore, Italian economic agents may be less sensitive to economic policy uncertainty shocks.

Second, there could be country-level differences in the accuracy with which the EPU index captures actual economic policy uncertainty. This is a relevant concern given that, as opposed to the US index, which is composed of newspaper articles from 10 newspapers, the European indices are constructed using only two newspapers. This could give a less accurate picture of actual economic policy uncertainty in some countries.

Third, dictated by the availability of the EPU index, the French sample is substantially longer than that of the other countries. While there are 348 observations and 3 NBER recessions in the sample for France, there are only 276 (Germany) or 228 (UK and Italy) observations and 2 NBER recessions in the other samples. Given the large size of the STVAR models considered in this paper, the larger sample size may result in a better ability to identify French parameters, because of reduced parameter uncertainty. Further, with a larger sample size, the impact of the used prior distribution is reduced, which may explain why the parameters in the countries with smaller samples are shrunk towards zero faster. Especially for the German estimates, this may be a potential explanation: the shapes of the impulse response functions look quite similar to French estimates, yet point estimates are of smaller magnitude and confidence bands are wider. To investigate whether these differences in results could indeed stem from different sample sizes, I re-estimated the French model using only the observations between 1993 and 2015[19]. The point estimates of effects on the US economic series indeed become smaller and insignificant. This supports the intuition that the samples of Germany, Italy and the UK may not have been large enough to find significant results.

7 Conclusions and discussion

This paper investigates the economic effects of increased economic policy uncertainty and provides new evidence on the effect of US and European economic policy uncertainty on the levels and growth rates of employment and industrial production in the US. Economic policy uncertainty in the US and four major European economies, France, Germany, Italy and the UK, is measured by the newspaper-based EPU index of Baker et al. (2016). Using monthly data from January 1987 to December 2015, smooth transition vector autoregressive models are estimated to allow for different dynamics between EPU and the macroeconomic variables throughout the business cycle. Dynamic effects of EPU shocks are examined using (generalised) impulse response functions.

The results of this paper concerning the effects of domestic economic policy shocks on the US economy are in line with the findings of Baker et al. (2016), providing evidence in favour of the proposition that economic policy uncertainty shocks in the US are followed by negative responses in the levels of US employment and industrial production. Extending the analysis beyond the scope of Baker et al. (2016)'s investigation, evidence is provided that due to cointegration between the variables, the effects of US EPU on economic level-series may even be permanent. Further, the results show negative effects of EPU shocks also on the growth rates of employment

[19] Results are available upon request

and industrial production. Although findings of previous literature suggested the presence of different dynamic effects throughout the business cycle, this paper finds no significant evidence that these effects are of different magnitudes during recessions and expansions.

Further, this paper extended the analysis by investigating the possibility that economic policy uncertainty shocks originating in Europe have adverse economic effects in the US through an uncertainty spillover channel and/or through an economic spillover channel. Although there is significant evidence of spillovers from European EPU to US EPU for all four countries, increases in US EPU are very small in magnitude. Hence, there is little empirical support for an uncertainty spillover channel through which economic policy uncertainty shocks from Europe could have negative economic effects in the US. There is some tentative evidence in support of the existence of an economic channel. Only for France, there is some evidence, significant only at a 68% confidence-level, that shocks in EPU have not only a negative effect on the domestic economy, but also negatively impact the growth rates of US employment, industrial production and exports of the US to France. As for domestic shocks, the found effects are virtually the same in either stage of the business cycle. Although the German economy also reacts significantly to German EPU shocks, there is no significant evidence that these negative economic effects spill over to the US. For Italy and the UK, there is little evidence that economic policy uncertainty shocks have any economic impact, even domestically.

Altogether, the point estimates of the effects of a one-standard deviation economic policy uncertainty shock originating in either the US or the European countries on economic growth in the US seem rather small, even when they are statistically significant at either confidence-level. The recent political events, however, have caused unprecedented high levels of EPU, including shocks that had sizes of more than three times the historical standard deviations which were considered in this paper. As a result of Brexit, for example, UK EPU increased by more than four and German EPU by more than six times their historical standard deviation, and in the month of the election of President Trump, the EPU indices of the US, Germany and France increased by more than 3 times their historical standard deviations. It is likely that shocks of such magnitude would propagate through the system completely differently than shocks related to purely domestic matters such as closely contested elections. Therefore, future research could extend on the research performed here and consider whether reactions to very large shocks – such as Brexit – differ from reactions to smaller shocks – such as tax reforms or closely contested elections – by introducing further non-linearity into the model. As the uncertainty shocks considered within this paper were thus comparably small, this renders the small magnitude of the point estimates of their effects plausible. Even if larger shocks propagated through the system identically to the smaller EPU shocks considered here, the recent political events would have resulted in impulse response estimates that are multiples of those found for one-standard deviation shocks in this paper.

Hence, the findings of this paper are relevant for policy-makers and give an economic reason to urge for quick resolution of current policy issues which are leading to very high levels of economic policy uncertainty. These results are not only important because of negative implications for the domestic economy. The finding that there are negative effects of a French EPU shock on economic growth in the US constitutes tentative evidence that such uncertainty-driven economic downturns could trigger downturns of economic conditions internationally.

This paper provided some interesting new findings, but also highlighted the need for further investigations of economic policy uncertainty and its effects. There remain some large limitations in using EPU indices for causal inference which necessitate caution in interpreting the findings of this and other papers. First, the magnitude of results are sensitive to the identification method used. There is tentative evidence that some findings in literature may be overstating the magnitude of negative economic effects of uncertainty as it is difficult to disaggregate economic policy uncertainty shocks from shocks that hit the economy directly. Second, economic effects of policy uncertainty may also be understated if increases in the EPU indices do not reflect the actual timing of uncertainty shocks. This could be the case if the public eye, and newspapers in particular, become interested in a policy uncertainty shock only months after it actually happened, while economic agents, such as firms and investors, adjusted their expectations and actions immediately. Then, any response to the actual policy uncertainty shock may have taken place before the shock can be observed as a spike in EPU. Take as an example the "fiscal cliff" which shows as a shock to US policy uncertainty in December 2012. The phenomenon was anticipated at least since 2010(Drawbaugh, 2012), and although news reports spiked prior to the beginning of 2013, it is unlikely that economic agents did not anticipate this uncertainty already long before December 2012. If markets are efficient, then stock-market based measures of uncertainty may capture the timing of shocks better.

Both of the above-mentioned points illustrate that EPU indices alone are not enough to identify causal effects of economic policy uncertainty. To identify the true timing of a shock, and to argue its exogeneity, experts and (human) reasoning are needed. It is clearly not an easy task to construct measures of such shocks, and hence it would be very time-consuming to construct such narrative policy uncertainty series over a long sample. Therefore, the framework of Stock and Watson (2018) seems promising also for future research: it allows use of the continuous EPU index to estimate the (endogenous) dynamic co-movement of macroeconomic variables and economic policy uncertainty over a long horizon, while a series of exogenous shocks can be used to identify instantaneous effects on a sub-sample.

This paper also opens up many other interesting directions for future research. First, this paper found some evidence indicating cointegration between macroeconomic level series and the EPU index. It could be interesting to investigate long-term equilibrium relationships between the US EPU index and macroeconomic variables as well as international EPU series. Second, there were few differences in dynamic responses between US expansions and recessions. This may be the result of the restrictions placed on the transition function due to the relatively short data-set, of the restriction of using only one transition function for all equations in the VAR, or of imposing that contemporaneous responses are the same in expansions and recessions. All three restrictions could be relaxed in future investigations. Last, more thorough investigations into the exact channels of the economic spillover of uncertainty may shed light on whether reduced import demand, foreign direct investment, returns to investment or other factors trigger economic spillover of uncertainty effects.

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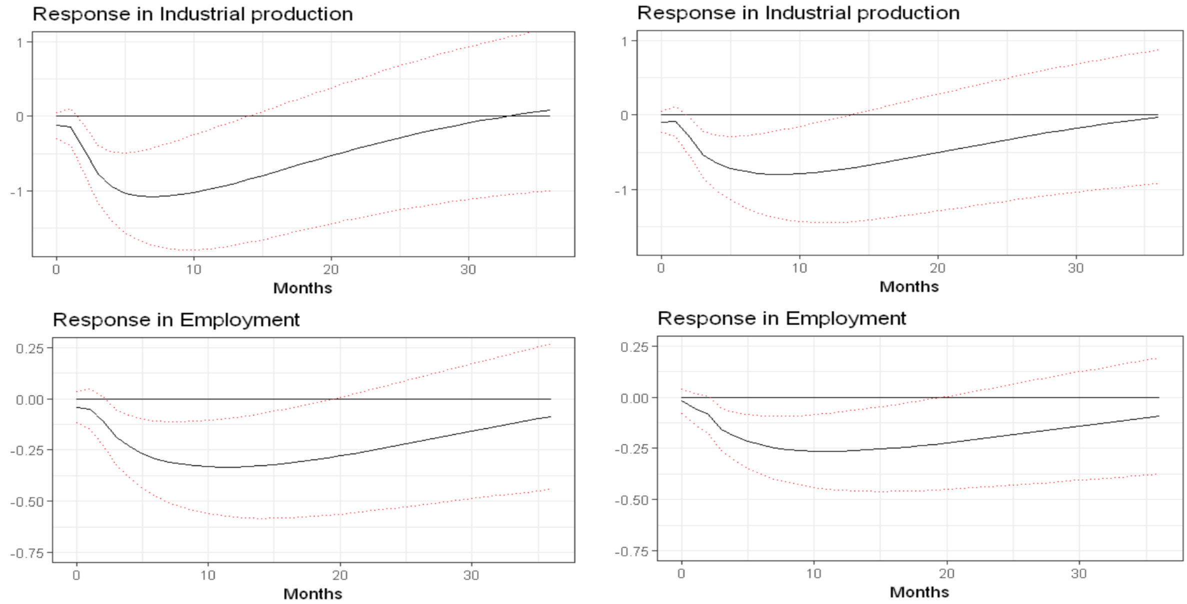
Appendix A: Replication of Baker et al. (2016)'s baseline results

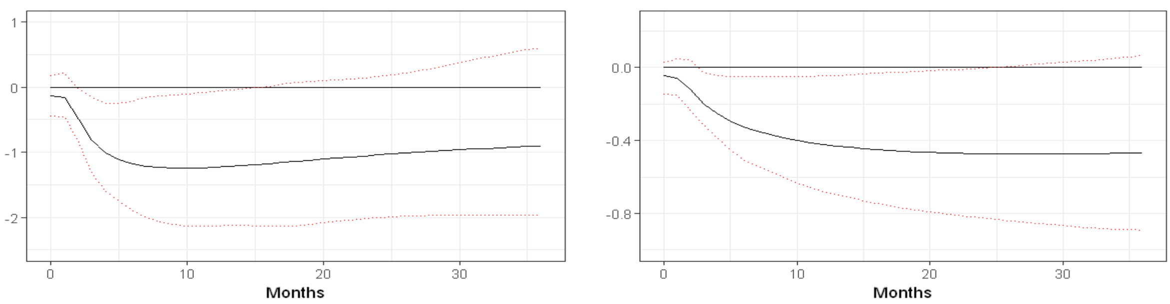


(a) IRFs using the Baker et al. (2016) data

(b) IRFs using this paper's data

Figure A.1: Impulse responses to an increase in EPU equivalent to the increase in mean from 2005-06 to 2011

This graph shows the impulse responses of the industrial production index and employment to an EPU shock equivalent to the increase in US EPU from its 2005-06 mean to its 2011 mean. The left panel uses the exact data used by Baker et al. (2016), where an older version of the EPU index seems to be used, and estimation is based on the sample 1985M01 - 2014M10. There, the shock corresponds to a 97.25 point increase in EPU. The right panel uses the data currently available on *policyuncertainty.com* and the main sample considered in this paper - 1987:01 to 2015:12 - where the shock corresponds to a 68.68 point increase in EPU. The red lines indicate 95% asymptotic confidence bands.



(a) Response in Industrial Production

(b) Response in Employment

Figure A.2: VECM Impulse responses to an increase in EPU equivalent to the increase in mean from 2005-06 to 2011

This graph shows the impulse responses of the industrial production index and employment to an EPU shock equivalent to the increase in US EPU from its 2005-06 mean to its 2011 mean, using the exact data of Baker et al. (2016). The estimated model is a VECM(3) with three cointegration relations. The red lines indicate 95% bootstrap confidence bands.

Appendix B: Dynamic factor model and identification of exogenous shocks

B.1: Dynamic factor model

B.1.1: State-space representation of the dynamic factor model

Below, the dynamic factor model described by (1), (2) and (3) is presented in state-space representation. Note that the notation largely follows Hamilton (1994).

$$\boldsymbol{EPU_t} = \boldsymbol{c} + \boldsymbol{H}\boldsymbol{\xi}_t + \boldsymbol{\omega_t}, \text{ where } \boldsymbol{\omega_t} \sim \boldsymbol{\mathcal{N}}(0, \boldsymbol{R}) \text{ and } t \in \{1, \dots, T\}, \tag{13}$$

$$\boldsymbol{\xi_{t+1}} = \boldsymbol{F}\boldsymbol{\xi_t} + \boldsymbol{v}_{t+1}, \text{ where } \boldsymbol{v_t} \sim \boldsymbol{\mathcal{N}}(0, \boldsymbol{Q}) \text{ and } t \in \{1, \dots, T\}, \tag{14}$$

where $\boldsymbol{EPU_t}$ is a $k \times 1$ vector of EPU realizations from k countries, the $3(k+2) \times 1$ state vector is given by $\xi_t = [C_t^{world}, C_t^{EU} u_{1t}, \dots, u_{kt}, C_{t-1}^{world}, \dots, u_{kt-1}, C_{t-2}^{world}, \dots, u_{kt-2}]'$, $\boldsymbol{H} = [\boldsymbol{H_1}, \boldsymbol{0}, \boldsymbol{0}]$ where

$$\boldsymbol{H_1} = \begin{bmatrix} \gamma_1 & 0 & 1 & \dots & 0 \\ \gamma_2 & 0 & 0 & \dots & 0 \\ & & \dots & & \\ \gamma_{m-1} & 0 & 0 & \dots & 0 \\ \gamma_m & \delta_m & 0 & \dots & 0 \\ & & \dots & & \\ \gamma_k & \delta_k & 0 & \dots & 1 \end{bmatrix}_{k \times (k+2)}$$

$$\text{and } \boldsymbol{F} = \begin{bmatrix} \boldsymbol{F_1} & \boldsymbol{F_2} & \boldsymbol{F_3} \\ \boldsymbol{I_{k+2}} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I_{k+2}} & \boldsymbol{0} \end{bmatrix}_{3(k+2) \times 3(k+2)} \quad \text{where } \boldsymbol{F_l} = \begin{bmatrix} \phi_{1l} & 0 & 0 & 0 & \dots & 0 \\ 0 & \phi_{2l} & 0 \dots & 0 & \dots & 0 \\ 0 & 0 & \rho_{1l} & 0 & \dots & 0 \\ \dots & & & & & \\ 0 & 0 & 0 & 0 & \dots & \rho_{kl} \end{bmatrix}_{(k+2) \times (k+2)},$$

and $\boldsymbol{R} = diag(\sigma_{\omega_1}^2, \dots, \sigma_{\omega_k}^2)$ and $\boldsymbol{Q} = diag(\sigma_{v_1}^2, \dots, \sigma_{v_{k+2}}^2, 0, \dots 0)$. For notational convenience, the m European series are ordered last.

B.1.2: Kalman Filter, Prediction and Smoothing equations

To obtain estimates of the state vector ξ_t, this paper uses the Kalman filter, prediction and smoothing equations. All equations necessary to recursively compute estimates can be found below, full derivations of these can be found in, for example, Hamilton (1994).

Let $\hat{\xi}_{t|t} = E(\xi_t | I_t)$, where I_t denotes all information up to period t, and let $P_{t|t} = E((\xi_t - \hat{\xi}_{t|t})(\xi_t - \hat{\xi}_{t|t})')$ denote the uncertainty in the estimate $\hat{\xi}_{t|t}$. Then it can be shown that the Kalman prediction-step estimates are given by:

$$\hat{\xi}_{t+1|t} = F\hat{\xi}_{t|t} \text{ and } P_{t+1|t} = FP_{t|t}F' + Q$$

The Kalman Filter-step estimates are given by:

$$\hat{\xi}_{t+1|t+1} = \hat{\xi}_{t+1|t} + P_{t+1|t}H'(HP_{t+1|t}H' + R)^{-1}(y_{t+1} - c - H\hat{\xi}_{t+1|t})$$

$$P_{t+1|t+1} = P_{t+1|t} - P_{t+1|t}H'(HP_{t+1|t}H' + R)^{-1}HP_{t+1|t}$$

The Kalman smoothing-step estimates are given by

$$\hat{\xi}_{t|T} = \hat{\xi}_{t|t} + P_{t|t}F'P_{t+1|t}^{-1}(\hat{\xi}_{t+1|T} - \hat{\xi}_{t+1|t}) \tag{15}$$

$$P_{t|T} = P_{t|t} - P_{t|t}F'P_{t+1|t}^{-1}(P_{t+1|t} - P_{t+1|T})P_{t+1|t}^{-1}FP_{t|t} \tag{16}$$

$$P_{t+1,t|T} = P_{t+1|T}P_{t+1|t}^{-1}FP_{t|t} \tag{17}$$

Given c, Q, R, H and F, $\hat{\xi}_{t|T}$ can be recursively estimated through these equations. The recursion is commonly started up with $\xi_{1|0} = 0$, the unconditional expected value of ξ. As uncertainty about this estimate is very high, $P_{1|0}$ gets a very large value (Hamilton, 1994).

B.1.3: Estimation algorithm[20]

The coefficients of u_{it} are set to 1 in (13) to identify the scale of the idiosyncratic components. Similarly, to identify the scale of the common components, I set $\gamma_m = 1$ and $\delta_m = 1$. Further, $c_i = \frac{1}{T}\sum_{t=1}^{T} EPU_{it}$ is set prior to estimation to reduce the number of parameters to be estimated. Nevertheless, (13) and (14) retain $6 * k + m + 8$ parameters to be estimated, alongside estimates for the state-vector ξ_t. Hence, the problem remains very large and maximum likelihood estimation in this model turned out to be very difficult. Instead, this paper therefore uses an Expectation-Maximization (EM) algorithm which relies on analytic solutions. The standard EM-implementation as, for example, derived by Digalakis et al. (1993) is based on the likelihood function

$$\begin{aligned} logL(\boldsymbol{EPU_{1:T}}, \boldsymbol{\xi_{0:T}}|\theta) = {} & \frac{T}{2}\log(|R^{-1}|) - \frac{1}{2}\sum_{t=1}^{T}(\boldsymbol{EPU}_t - \boldsymbol{c} - \boldsymbol{H\xi}_t)'R^{-1}(\boldsymbol{EPU}_t - \boldsymbol{c} - \boldsymbol{H\xi}_t) \\ & + \frac{T}{2}\log(|Q^{-1}|) - \frac{1}{2}\sum_{t=1}^{T}(\boldsymbol{\xi_t} - \boldsymbol{F\xi_{t-1}})'Q^{-1}(\boldsymbol{\xi_t} - \boldsymbol{F\xi_{t-1}}) \end{aligned} \tag{18}$$

and the idea that given ξ_t, maximization in (18) is simple and allows for analytical solutions for F, H, c, R and Q. The standard algorithm, however, does not incorporate parameter restrictions that are necessary in the given context to enforce that some elements of H and F can be set to zero and one.

To solve this issue, I derive the following restricted EM-algorithm[21]: Note that given ξ, opti-

[20] All methods have been implemented by the author in R, the code can be made available upon request.

[21] I would like to thank dr. R. Lange, with whom I had a very interesting discussion about how to adapt the

mization of (18) with respect to H and F corresponds to the system OLS estimator. As R and Q are diagonal by assumption, the rows of F and H can be estimated equation by equation. Let ξ_t^P denote the set of passive elements of ξ in equation i, that is the states with fixed coefficients, while ξ_t^A summarizes the set of states that are active in the estimation. The optimization problem for the i^{th} row of H can be written as

$$\begin{aligned} \min \sum_{t=1}^{T} (EPU_{it} - H_i\xi_t)'(EPU_{it} - H_i\xi_t) = \\ \min \sum_{t=1}^{T} (EPU_{it} - H_i^P\xi_t^P - H_i^A\xi_t^A)'(EPU_{it} - H_i^P\xi_t^P - H_i^A\xi_t^A) \end{aligned} \tag{19}$$

where for notational convenience the constant c has been omitted. Then

$$\frac{\partial}{\partial H_i^A} = \sum_{t=1}^{T} (EPU_{it}\xi_t^{A'} - H_i^P(\xi_t^P\xi_t^{A'})) - H_i^A(\sum_{t=1}^{T} \xi_t^A\xi_t^{A'})$$

Taking expectations and solving for H_i^A yields:

$$H_i^A = \sum_{t=1}^{T} (EPU_{it}\hat{\xi}_{t|T}^{A'} - H_i^P(\hat{\xi}_{t|T}^P\hat{\xi}_{t|T}^{A'} + P_{t|T}^{(P,A)}))(\sum_{t=1}^{T} \hat{\xi}_{t|T}^A\hat{\xi}_{t|T}^{A'} + P_{t|T}^{(A,A)}))^{-1} \tag{20}$$

where $P_{t|T}^{(x,y)}$ refers to the selection of rows corresponding to set x and columns corresponding to set y of the matrix $P_{t|T}$. The derivation of the restricted estimator of F proceeds analogously.

The employed EM algorithm iterates over two steps:

1. E-Step: use smoothing equations (15), (16) and (17) presented in section B.1.2 to obtain estimates of $\hat{\xi}_{t|T}$, $P_{t|T}$ and $P_{t,t-1|T}$

2. M-Step: Estimate the active elements of H and F row-by-row as:

$$H_i^A = \sum_{t=1}^{T} ((EPU_{it} - c_i)\hat{\xi}_{t|T}^{A'} - H_i^P(\hat{\xi}_{t|T}^P\hat{\xi}_{t|T}^{A'} + P_{t|T}^{(P,A)}))(\sum_{t=1}^{T} \hat{\xi}_{t|T}^A\hat{\xi}_{t|T}^{A'} + P_{t|T}^{(A,A)}))^{-1}$$

$$F_i^A = \sum_{t=1}^{T} ((\hat{\xi}_{it|T})\hat{\xi}_{t|T}^{A'} + P_{t,t-1|T}^{(i,A)})(\sum_{t=0}^{T-1} \hat{\xi}_t^A\hat{\xi}_t^{A'} + P_{t|T}^{(A,A)})^{-1}$$

   Use the elements on the main diagonal of the standard unrestricted R and Q estimates to get the (restricted) diagonal estimates.

$$\begin{aligned} Q_{unres} = \frac{1}{T}\sum_{t=1}^{T} (\hat{\xi}_{t|T}\hat{\xi}_{t|T}' + P_{t|T} - F(\hat{\xi}_{t-1|T}\hat{\xi}_{t|T}' + P_{t-1,t|T}) - \\ (\hat{\xi}_{t|T}\hat{\xi}_{t-1|T}' + P_{t,t-1|T})F' + F(\hat{\xi}_{t-1|T}\hat{\xi}_{t-1|T} + P_{t-1|T})F') \end{aligned} \tag{21}$$

standard EM-algorithm to allow for simple incorporation of restrictions. This greatly helped me in deriving the restricted EM algorithm presented here

$$
\begin{aligned}
R_{unres} = \frac{1}{T}\sum_{t=1}^{T}((\boldsymbol{EPU}_t - \boldsymbol{c})(\boldsymbol{EPU}_t' - \boldsymbol{c}) - H\hat{\xi}_{t|T}(\boldsymbol{EPU}_t - \boldsymbol{c})' \\
-(\boldsymbol{EPU}_t - \boldsymbol{c})\hat{\xi}_{t|T}'H' + H(\hat{\xi}_{t|T}\hat{\xi}_{t|T}' + P_{t|T})H')
\end{aligned}
\tag{22}
$$

Initial estimates for F, H, Q, and R are made randomly. To avoid convergence to local optima, multiple random starting points are investigated and the parameters producing the highest likelihood-value are chosen.

B.2: Graphical representation of dynamic factor model estimates

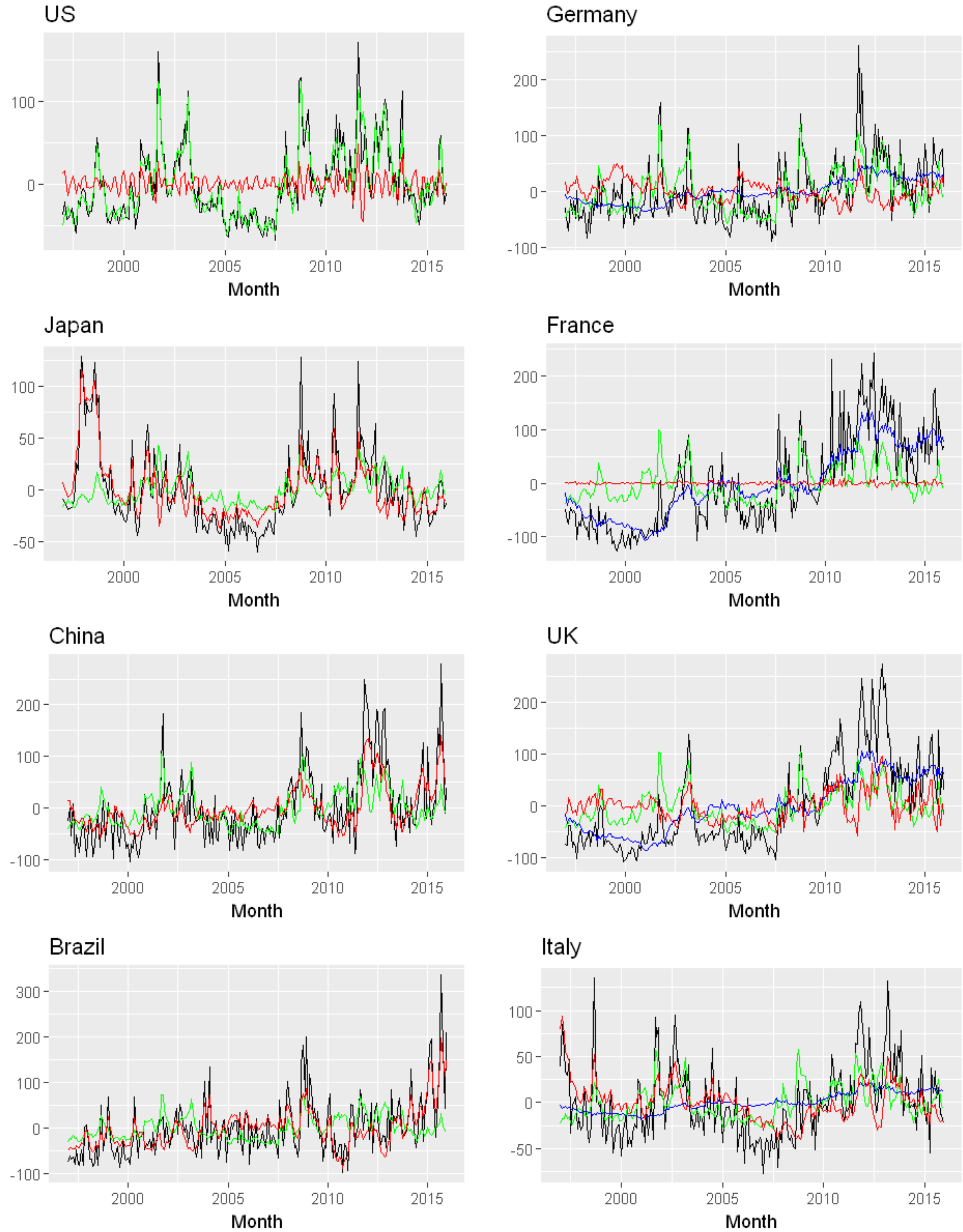


Figure B.1: Latent common and idiosyncratic components in a dynamic factor model for EPU
This figure shows the demeaned EPU series, that is $EPU_i - \hat{c}_i$(black), and the parts explained by the "world uncertainty" component, that is $\hat{\gamma}_i \hat{C}^{world}$ (green), the European uncertainty component, that is $\hat{\delta}_i \hat{C}^{EU}$ (blue), and the idiosyncratic component, that is $\hat{u}_i$ (red), for a sample of eight countries between 1997M01 and 2015M12. For interpretability of the colours, refer to a digital version of this paper.

B.3: Dummy series of exogenous uncertainty shocks and related events

This section briefly describes events whose timing can be related to large shocks in the idiosyncratic uncertainty series. The shocks considered are the standardised residuals with value larger than 1.64, which corresponds to the 95% percentile of the normal distribution. Unless otherwise indicated, events related to EPU spikes were identified using the classification provided by Baker et al. (2016). Unfortunately, not all large residuals could be related to specific events.

Interestingly, the dummy series constructed for the US is very similar to a dummy series of large EPU shocks constructed by Caggiano et al. (2017a). This is interesting given that distinct methodologies were used to obtain these dates: while this paper uses the largest realisations of the error term from the US idiosyncratic component in a dynamic factor model, they used the Hodrick-Prescott filter to obtain the dates from the largest realisations of the cyclical component in EPU.

US Shocks

- 2000M11: Election of president Bush.[22]
- 2001M09: Shock related to the aftermath of the September 11 terrorist attacks
- 2008M09: Collapse of the Lehman brothers. Due to its direct economic impact, this event is not included as a dummy
- 2010M07 and 2010M09: These shocks are classified as the run-up to the 2010 midterm election by Caggiano et al. (2017a).
- 2011M07 and 2011M08: Debt ceiling debate in congress.
- 2012M12: Shock related to the Fiscal cliff, which refers to a set of tax-cuts expiring in January 2013
- 2013M09 and 2013M10: In October 2013, a government shut-down took place in the US.
- Shocks without classification: 2014M06, 2015M08

French Shocks

- 2004M04: Regional elections in which the UMP had record-low vote shares
- 2004M11: Sarkozy becomes chairman of the UMP.
- 2007M09: The Northern Rock bank enters a crisis and a bank run ensues in the UK. As this uncertainty shock originates in the UK, it is excluded from the French dummy series.
- 2010M10: A proposed reform of the social security system related to an increase in the retirement age causes a month of strikes and protests(Clark, 2010).

[22]This shock was not part of the largest residuals, yet it did show as a large residual and one of the largest spikes in the idiosyncratic uncertainty series, and was included in the dummy series identified by Caggiano et al. (2017a). As it is a shock that is arguably exogenous to macroeconomic series, I decided to include it too.

- 2012M04 and 2012M06: Elections for parliament and president
- Large shocks without clear classification: 1998M04, 2009M11, 2010M05, 2010M12, 2011M03, 2013M06, 2015M06, 2015M07

German Shocks

- 1999M08: Large discussions and protests about the "Sparpaket", a tax reform proposed by the new government (Tagesspiegel, 1999)
- 2001M09 and 2010M10: Aftermath of the September 11 terrorist attacks. These shocks are not included into the German dummy series given that it originated in US uncertainty.
- 2003M02: Regional election sees the current ruling party lose their majority in the *Bundesrat*(Forschungsgruppe Wahlen E.V., 2003)
- 2005M09: Chancellor Schröder loses to Angela Merkel in the General election after he lost a vote of no confidence in the Bundestag.
- 2007M09: The Northern Rock bank enters a crisis and a bank run ensues in the UK. As this uncertainty shock originates in the UK, it is excluded from the German dummy series
- 2011M08 and 2011M09: Worsening of the Euro crisis. As this has direct economic effects, this shock is not included in the dummy series.
- Shocks without classification: 1999M06, 2015M06, 2015M10

Italian Shocks

- 1998M08 and 1998M09: Russian crisis. Due to its potential direct economic effects, this shock is not included in the dummy series.
- 2001M09: September 11 terrorist attacks. This shocks is not included into the Italian dummy series given that it originated in US uncertainty.
- 2001M11 and 2002M06: A change of the Italian labor law, which became known as the Biagi reform, was introduced in late October 2001. This lead to huge resistanceand the killing of economic policy advisor Biagi in March 2002(Tiraboschi, 2005). After months of strikes and protests, the government and labor unions reached a controversial agreement in June 2002 (Quigley, 2003).
- 2011M10 and 2011M11: The euro crisis worsens and Berlusconi steps down. As the Euro crisis has direct economic effects, this shock is not included in the dummy series.
- 2013M01, M02 and M03: The general election in January 2013 led to a stalemate in Italian politics as the elected parties could not form a government (Stratfor, 2013)
- Shocks without classification: 2002M09, 2004M07,2013M11, 2014M11

UK Shocks

- 2007M09[23]: The Northern Rock bank enters a crisis and a bank run ensues in the UK(The Guardian, 2008). As the bank could rely on the bank of England as lender of last resort, there were no direct economic effects of this crisis in September, except those caused by the loss in confidence of shareholders and depositors due to uncertainty about the future of the bank.
- 2011M10 and 2011M11: Worsening of the Euro crisis. As this has direct economic effects, this shock is not included in the dummy series.
- 2014M08 and 2014M09: The Scottish referendum for independence takes place in September, and the opinion polls became less clear-cut closer to the election date (McInnes and Ayres, 2014)
- 2015M04: General election in the UK with very close pre-election polls and an unexpected majority of the conservatives (The Economist, 2015)
- Shocks without classification: 2008M03, 2010M08 and 2010M10; 2012M05, M09, M10 and M11; 2015M09.

[23] This date did not show as a large shock in idiosyncratic uncertainty of the UK. It did, however, show as a large shock in “European uncertainty”. As the shock can be said to have originated in the UK, I decided to include it into the dummy series of the UK.

Appendix C: Terasvirta and Yang (2014) test for non-linearity

C.1: Test procedure

This section shortly summarizes the test of Terasvirta and Yang (2014) for presence of non-linearity. To establish the testing procedure, note that Model (6) can be rewritten as

$$\boldsymbol{Y_t} = \boldsymbol{B_1 X_t} + F(Z_{t-1})\boldsymbol{B_2 X_t} + \boldsymbol{u_t} \tag{23}$$

with $\boldsymbol{B_1} = [c_R, A_{1,R}, \ldots, A_{p,R}]$, $\boldsymbol{B_2} = [c_E - c_R, A_{1,E} - A_{1,R}, \ldots, A_{p,E} - A_{p,R}]$ and $\boldsymbol{X_t} = [1, \boldsymbol{Y}_{t-1}, \ldots, \boldsymbol{Y}_{t-p}]$. As under the null hypothesis of $\boldsymbol{B_1} = \boldsymbol{B_2}$ parameters γ and c are not identified, we use the n-order Taylor approximation of $F(Z_{t-1})$ around $\gamma = 0$ to test for non-linearity:

$$F(Z_{t-1}|\gamma, c) = \sum_{i=0}^{n} a_{n-i} Z_{t-1}^{n-i} + r_t \tag{24}$$

where the a_{n-i} are coefficients and r_t is the remainder term. Substituting this term into (23) yields

$$\boldsymbol{Y_t} = \boldsymbol{B_1 X_t} + \left(\sum_{i=0}^{n} a_{n-i} Z_{t-1}^{n-i} + r_t \right) \boldsymbol{B_2 X_t} + \boldsymbol{u_t} = \Theta_0 \boldsymbol{X_t} + \sum_{i=1}^{n} \Theta_i \boldsymbol{X_t} Z_{t-1}^{i} + \boldsymbol{u_t *} \tag{25}$$

Under the null hypothesis of linearity, $\Theta_1 = \ldots = \Theta_n = \mathbf{0}$. Terasvirta and Yang (2014) suggest a Lagrange multiplier type test to establish linearity:

1. Estimate the restricted model by regressing $\boldsymbol{Y}_t$ on $\boldsymbol{X}_t$ with residuals $\hat{\boldsymbol{e}}_t$. Calculate the matrix of the sum of squared residuals $SSR_0 = \sum_{t=1}^{T} \hat{\boldsymbol{e}}_t (\hat{\boldsymbol{e}}_t)'$
2. Regress $\hat{\boldsymbol{e}}_t$ on $[\boldsymbol{X_t}, \boldsymbol{X_t} Z_{t-1}, \ldots, \boldsymbol{X_t} Z_{t-1}^{n}]$, obtain residuals $\tilde{\boldsymbol{e}}_t$ and calculate the matrix of the sum of squared residuals $SSR_1 = \sum_{t=1}^{T} \tilde{\boldsymbol{e}}_t (\tilde{\boldsymbol{e}}_t)'$
3. The test statistic is then given by $LM_n = T(k - tr(RSS_0^{-1} RSS_1))$ and follows a χ^2 distribution with $nk(kp+1)$ degrees of freedom.

C.2: Test results

Table 2: Test-statistics for the Terasvirta and Yang (2014) test

	US	France	Germany	Italy	UK
1	181.27***	286.12***	330.72***	299.16***	279.17***
2	333.47***	511.13***	538.54***	505.47***	490.89***
3	431.24***	687.98***	703.45***	701.22***	677.11***
4	525.23***	868.07***	916.12***	865.36***	842.12***
5	626.33***	1035.35***	1069.83***	1018.25***	NaN

For the US, this tests the null hypothesis of linearity in a VAR(3) for vector $\boldsymbol{Y}_t = [EPU_t^{US}, \Delta log(SP500_t), \Delta FFR_t, \Delta log(Empl_t), \Delta log(IP_t)]$ against the alternative of non-linearity. For France, Germany, Italy and the UK, the vector of variables is augmented and becomes $\boldsymbol{Y}_t = [EPU_t^{US}, EPU_t^i, \Delta log(IP_t^i), \Delta log(SP500_t), \Delta FFR_t, \Delta log(Empl_t), \Delta log(IP_t)]$, where i can be replaced by the respective countries.
*** denotes significance at a 1% confidence-level. NaN indicates that the system was numerically singular, hence no test statistic could be computed.

Appendix D: Material relating to generalised impulse response functions[24]

D.1.: GIRF estimation procedure

Step 1: Generation of parameter estimates using the Gibbs sampler

Step 1.1: Estimate γ and c using the iterative NLS procedure discussed in section 5.1. Use the NLS estimate as a starting value for $\boldsymbol{B}$

Step 1.2: Draw $\Sigma|\boldsymbol{B},\gamma,c$ from $IW(EE',T)$, where $EE' = (\boldsymbol{y}-\boldsymbol{BX})(\boldsymbol{y}-\boldsymbol{BX})'$

Step 1.3: Draw $vec(\boldsymbol{B})|\Sigma,\gamma,c$ from $N(\bar{b},\bar{\boldsymbol{V}})$, where $\bar{b}$ and $\bar{\boldsymbol{V}}$ are defined as in section 5.1.

Step 1.4: Repeat steps 1.2 and 1.3 10,200 times. Discard the first 200 estimates and store the others for further use.

Step 2: Computation of Generalised impulse responses

Step 2.1: Draw a realisation j of $\boldsymbol{B}$ from the chain of estimates generated in Step 1. Use the drawn realisation $\boldsymbol{B}_j$ and the estimated γ and c to compute all T reduced form residuals $\hat{\boldsymbol{u}}_t$. Compute $H_{.i}$ element-wise as $\hat{H}_{ki} = \frac{E(\hat{u}_{kt}Z_t)}{E(\hat{u}_{it}Z_t)} = \frac{\hat{\boldsymbol{u}}_i^T\boldsymbol{Z}}{\hat{\boldsymbol{u}}_j^T\boldsymbol{Z}}$ where i is the shocked variable.[25]

Step 2.2: Randomly select starting time t from the set of t for which $F(Z_{t-1}) \leq 0.5$.

Step 2.3: Draw, with replacement, a sequence of H residuals from the constructed reduced form residuals. Use these residuals and $\boldsymbol{B_j}$ to simulate sequence of the variables of interest, $\boldsymbol{y}_t^*,\ldots,\boldsymbol{y}_{t+h}^*$.

Step 2.4: Replace the first residual in the series drawn in step 2.3 by $\boldsymbol{u}_t^{\boldsymbol{\delta},*} = \boldsymbol{u}_t^* + H_{.i}\delta$. Compute a new sequence of variables, $\boldsymbol{y}_t^{\boldsymbol{\delta},*},\ldots,\boldsymbol{y}_{t+h}^{\boldsymbol{\delta},*}$.

Step 2.5: Repeat steps 2.2 to 2.4 for $m = 200$ replications. Compute $GIRF(h,\delta,Recession,\boldsymbol{B_j})$ as:

$$GIRF(h,\delta,Recession,\boldsymbol{B_j}) = \frac{1}{m}\sum_{l=1}^{m}(\boldsymbol{y}_{t+h}^{\boldsymbol{\delta},*} - \boldsymbol{y}_{t+h}^*), \text{ for } h \in 0,\ldots,H$$

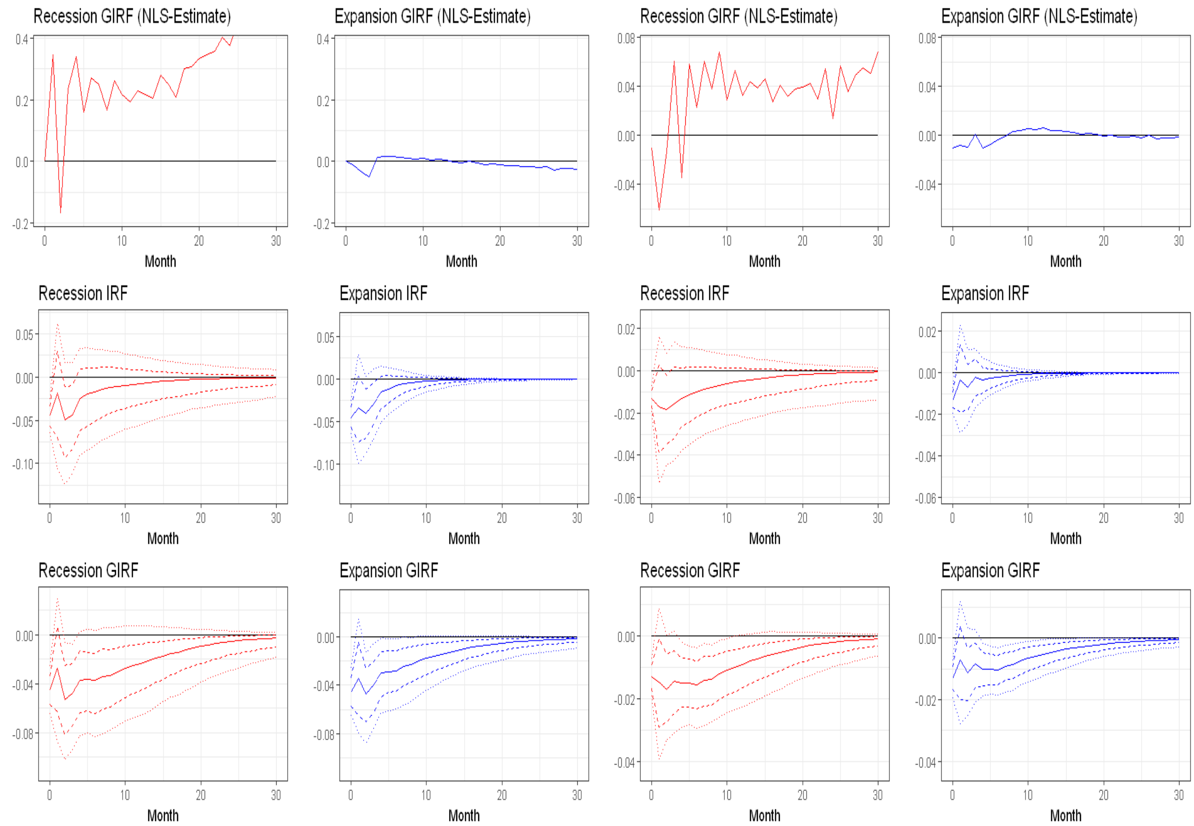
Step 2.6: Repeat steps 2.3 to 2.5 analogously but select only t for which $F(Z_{t-1}) > 0.5$. This gives an estimate for $GIRF(h,\delta,Expansion,\boldsymbol{B_j})$

Step 3: Repeat steps 2.1 to 2.6 for 1000 randomly drawn realisations of the lag-polynomials. Re-compute matrix H for each realisation. The same random seed is used in drawing realisations of t and residuals for each of the 1000 replications. The final estimate of the two GIRFs is the median of the 1000 realisations and confidence bands can be computed as the respective quantiles of the 1000 estimates.

[24] All methods have been implemented by the author in R, the code can be made available upon request.

[25] Whenever a Cholesky decomposition was used in this paper, $H_{.i}$ was replaced by the i^{th} column of $\boldsymbol{P}$, the lower-triangular Cholesky decomposition of the variance-covariance matrix of reduced-form errors.

D.2: Comparison of different types of impulse response functions



(a) IP growth rate (in percent) (b) Employment growth rate (in percent)

Figure D.1: Impulse responses to a one-standard deviation shock to US EPU

This graph shows the responses of the growth rates in IP and Employment to a one-standard deviation shock to US EPU (40.18 points). Parameters were estimated over the sample January 1987 to December 2015 in a STVAR(3). Orthogonalised impulse responses are computed on basis of the Cholesky decomposition on basis of the ordering $[EPU_t^{US}, \Delta log(SP500_t), \Delta FFR_t, \Delta log(Empl_t), \Delta log(IP_t)]$. The first row represents the GIRF based on the NLS-estimate of the model, where parameter uncertainty is not taken into account. The second row represents the IRF estimates based on the assumption that the state on the economy remains constant during the considered time period. The third row represents the GIRF estimates on basis of the Bayesian estimation of parameters. For the bottom two rows, the solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the posterior distributions, and dotted lines represent the 5th and 95th percentile.

Figure D.1 displays the different types of impulse response functions for a one-standard deviation shock to US EPU in expansions and recessions. The upper panels show the GIRFs based on only the NLS estimate of the STVAR. Clearly, given the estimates, and the estimate for the recession regime in particular, shocks seem to be permanent and propagation explosive. As there are very few observations in recessions, this effect may stem to a large extent from bad identification of the parameter matrices. This illustrates both the necessity of incorporating the parameter uncertainty into the confidence intervals of the GIRFs and the usefulness of Bayesian estimation with shrinkage prior. The middle panels show the impulse response functions based on the assumption that the regime will stay constant, as for example assumed by Auerbach and Gorodnichenko (2012) and Fontaine et al. (2017), where estimates and confidence intervals are based on draws from the simulated posterior distribution of the parameters. While the point estimates of the IRFs for the IP growth rate are quite similar for both regimes, the confidence bands during expansions are much more narrow after 6 months than during a recession, indicating a faster disappearance of uncertainty effects during expansions. For the employment growth rate, the point estimate during recessions indicates a substantially larger negative effect than the point estimate during expansions. Although the point estimates indicate a negative reaction of both macroeconomic series, neither are significantly different from zero. The bottom panel shows the GIRFs which are considered in this paper. As a result of differing treatment of future shocks and of allowing observations to lie in-between recessions and expansions, the GIRFs for expansion and recession look much more alike than the IRFs. As opposed to the IRF estimates, the GIRF estimates indicate significant effects of an EPU shock on both IP and employment growth.

Appendix E: Full results

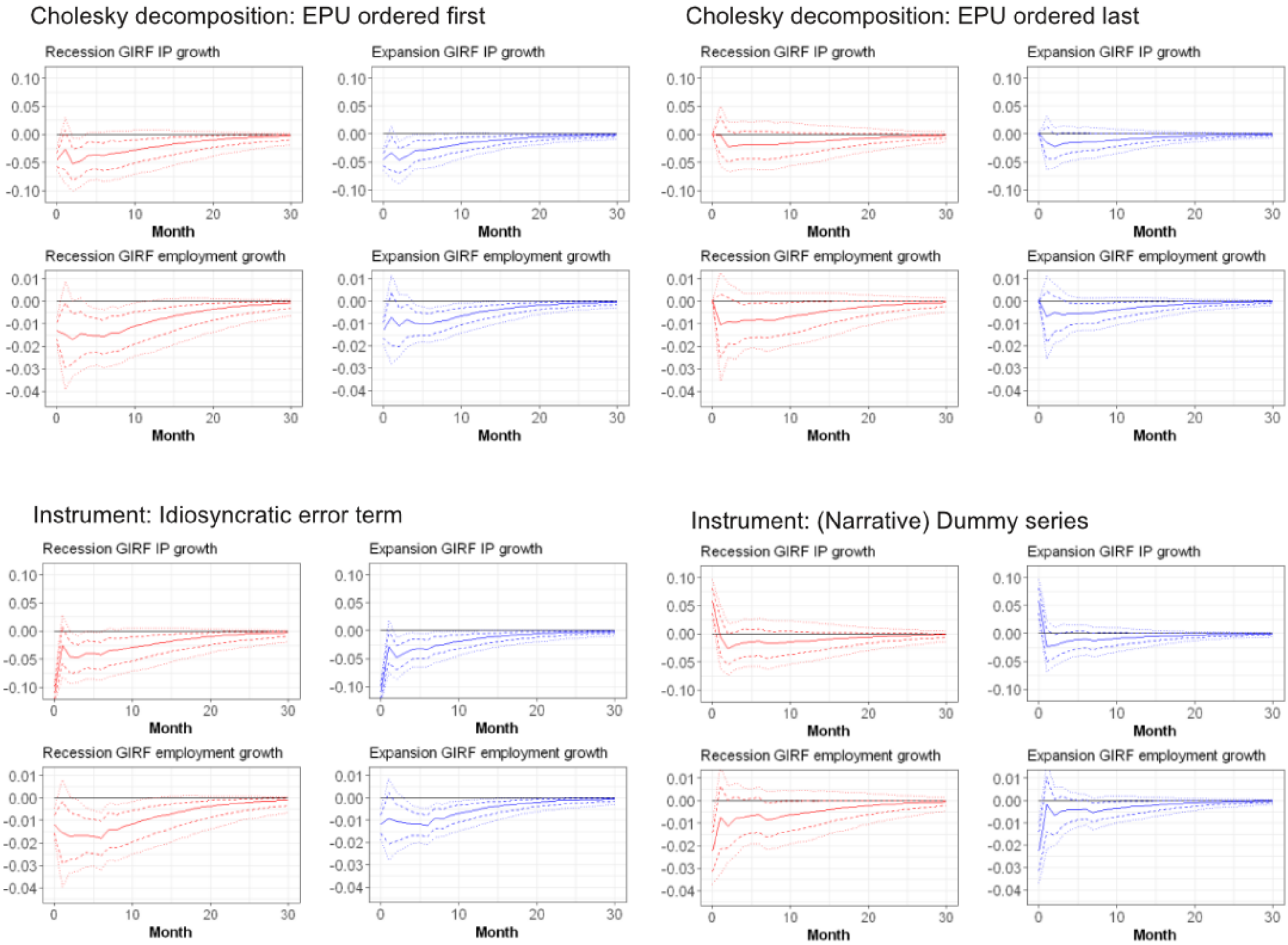


Figure E.1: Generalised impulse responses to a one-standard deviation shock to US EPU using different identification methods

This graph shows the responses of the growth rate in IP and Employment to a one-standard deviation shock to US EPU (40.18 points). All growth rates were multiplied by 100 to allow for interpretation in percent. The impulse response functions in the top left corner use a Cholesky decomposition with EPU ordered first, the top right corner uses a Cholesky decomposition with EPU ordered last. The bottom row of impulse response functions uses external instruments for identification: the idiosyncratic error term from a dynamic factor model on the left side, and a dummy series on the right side. Parameters were estimated over the sample January 1987 to December 2015. The solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the simulated posterior distributions, and dotted lines represent the 5th and 95th percentile.

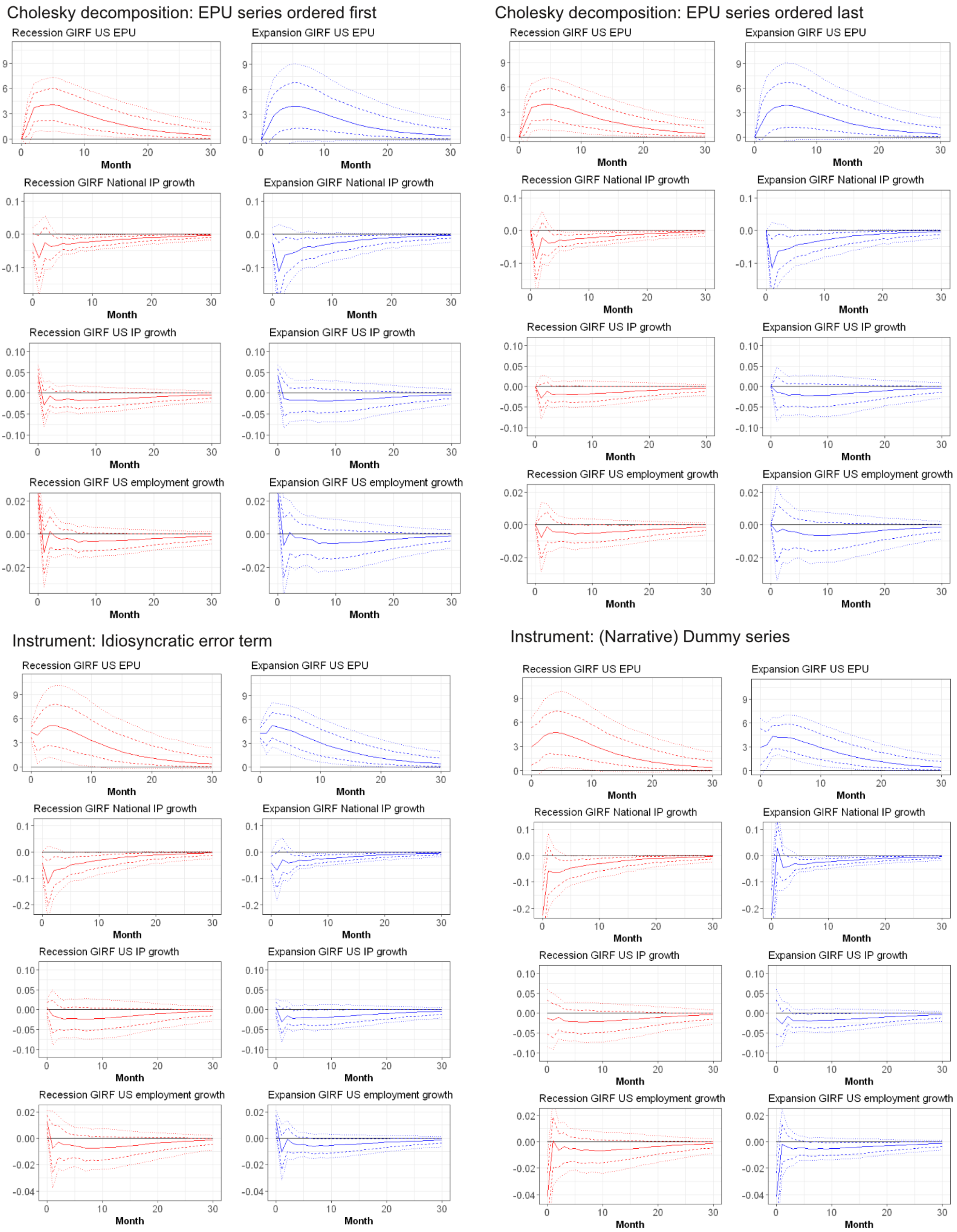


Figure E.2: Generalised impulse responses to a one-standard deviation shock to French EPU using different identification methods

This graph shows the responses of US EPU and the growth rate in IP and Employment to a one-standard deviation shock to French EPU (74.51 points). All growth rates were multiplied by 100 to allow for interpretation in percent. The impulse response functions in the top left corner use a Cholesky decomposition with French EPU ordered second after US EPU, the top right corner uses a Cholesky decomposition with US EPU and French EPU ordered last. The bottom row of impulse response functions uses external instruments for identification: the idiosyncratic error term from a dynamic factor model on the left side, and a dummy series on the right side. Parameters were estimated over the sample January 1987 to December 2015. The solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the simulated posterior distributions, and dotted lines represent the 5th and 95th percentile.

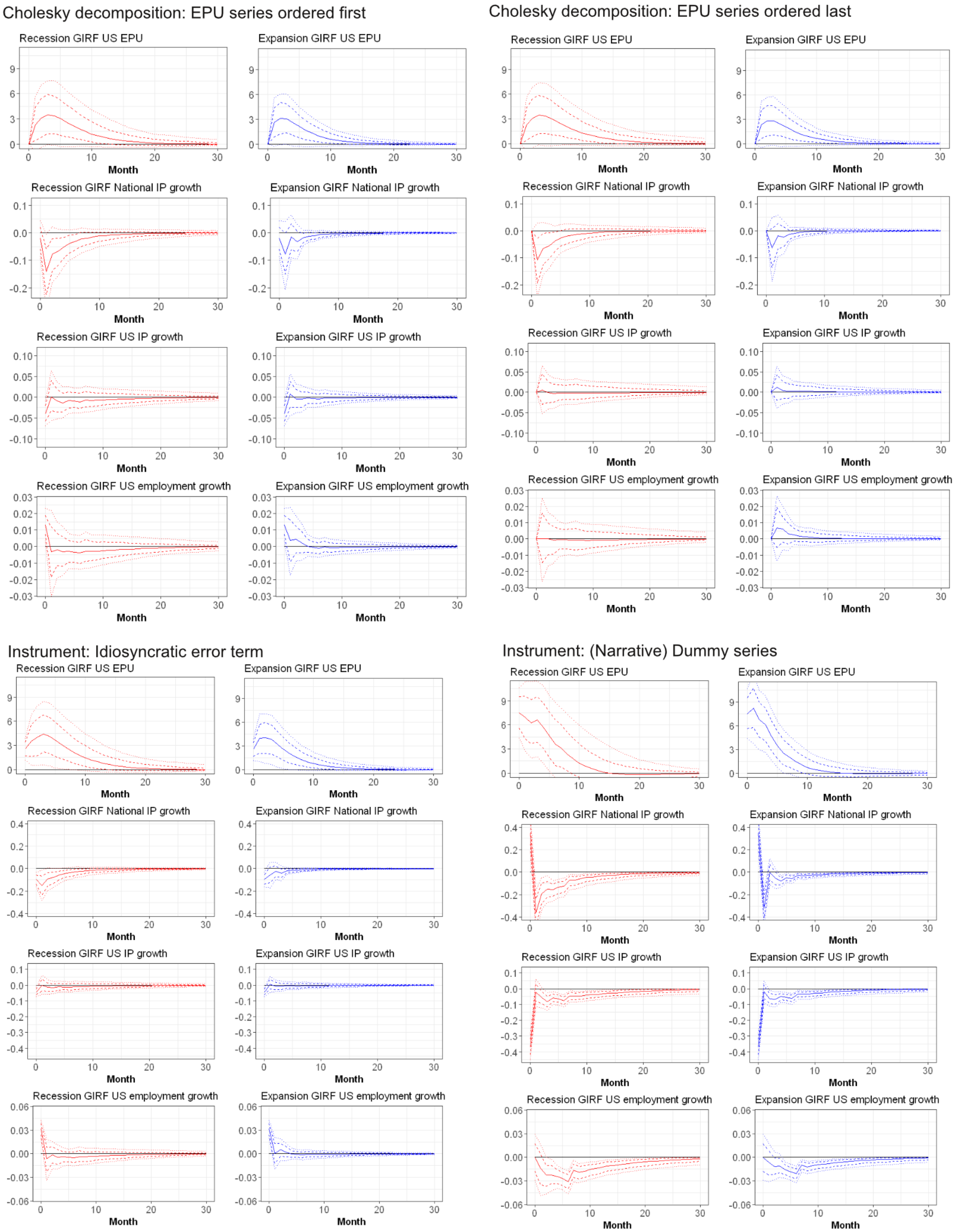


Figure E.3: Generalised impulse responses to a one-standard deviation shock to German EPU using different identification methods

This graph shows the responses of US EPU and the growth rate in IP and Employment to a one-standard deviation shock in German EPU (51.86 points). All growth rates were multiplied by 100 to allow for interpretation in percent. The impulse response functions in the top left corner use a Cholesky decomposition with German EPU ordered second after US EPU, the top right corner uses a Cholesky decomposition with US EPU and German EPU ordered last. The bottom row of impulse response functions uses external instruments for identification: the idiosyncratic error term from a dynamic factor model on the left side, and a dummy series on the right side. Parameters were estimated over the sample January 1993 to December 2015. The solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the simulated posterior distributions, and dotted lines represent the 5th and 95th percentile.

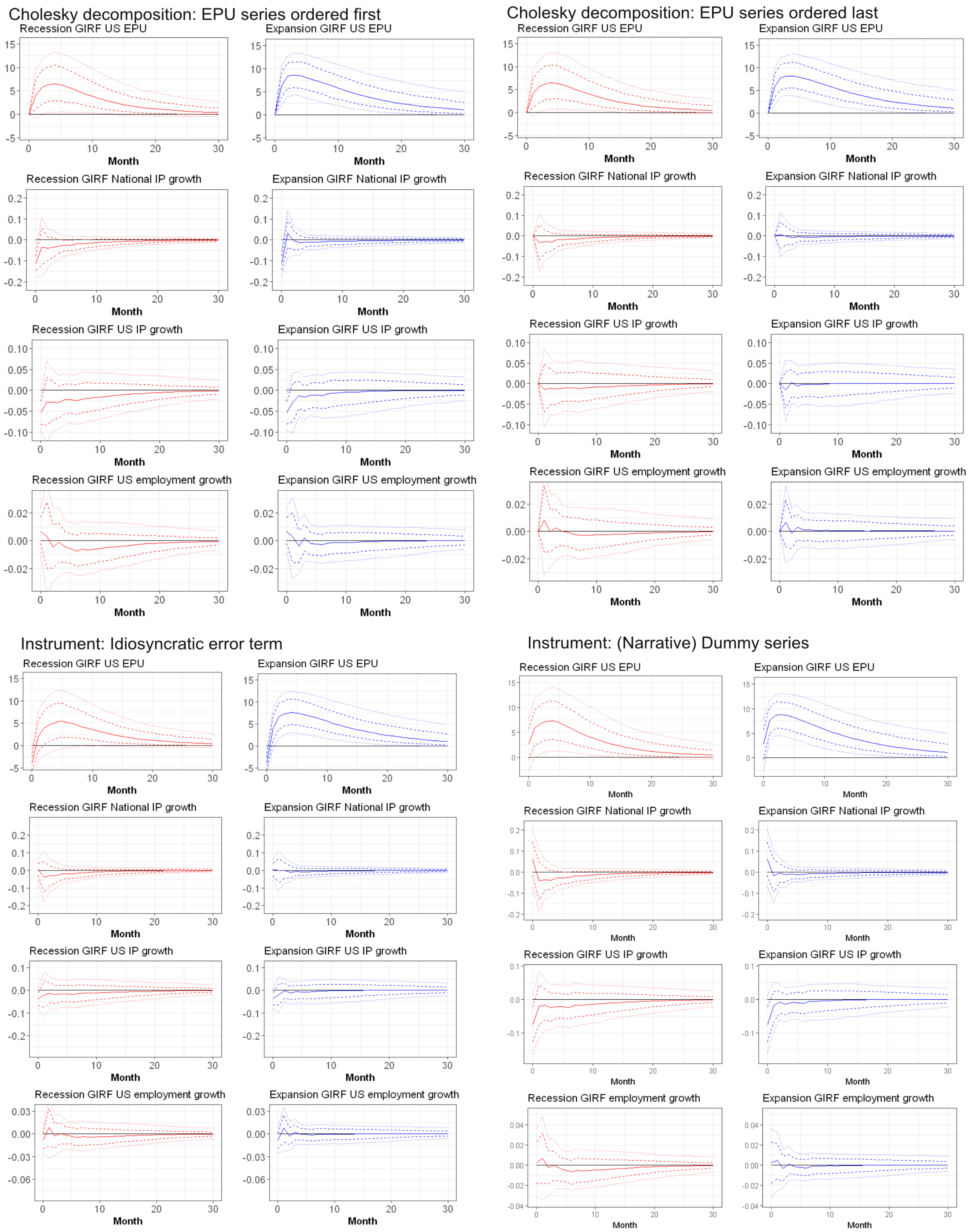


Figure E.4: Generalised impulse responses to a one-standard deviation shock to UK EPU using different identification methods

This graph shows the responses of US EPU and the growth rate in IP and Employment to a one-standard deviation shock to UK EPU (83.84 points). All growth rates were multiplied by 100 to allow for interpretation in percent.The impulse response functions in the top left corner use a Cholesky decomposition with UK EPU ordered second after US EPU, the top right corner uses a Cholesky decomposition with US EPU and UK EPU ordered last. The bottom row of impulse response functions uses external instruments for identification: the idiosyncratic error term from a dynamic factor model on the left side, and a dummy series on the right side. Parameters were estimated over the sample January 1997 to December 2015. The solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the simulated posterior distributions, and dotted lines represent the 5th and 95th percentile.

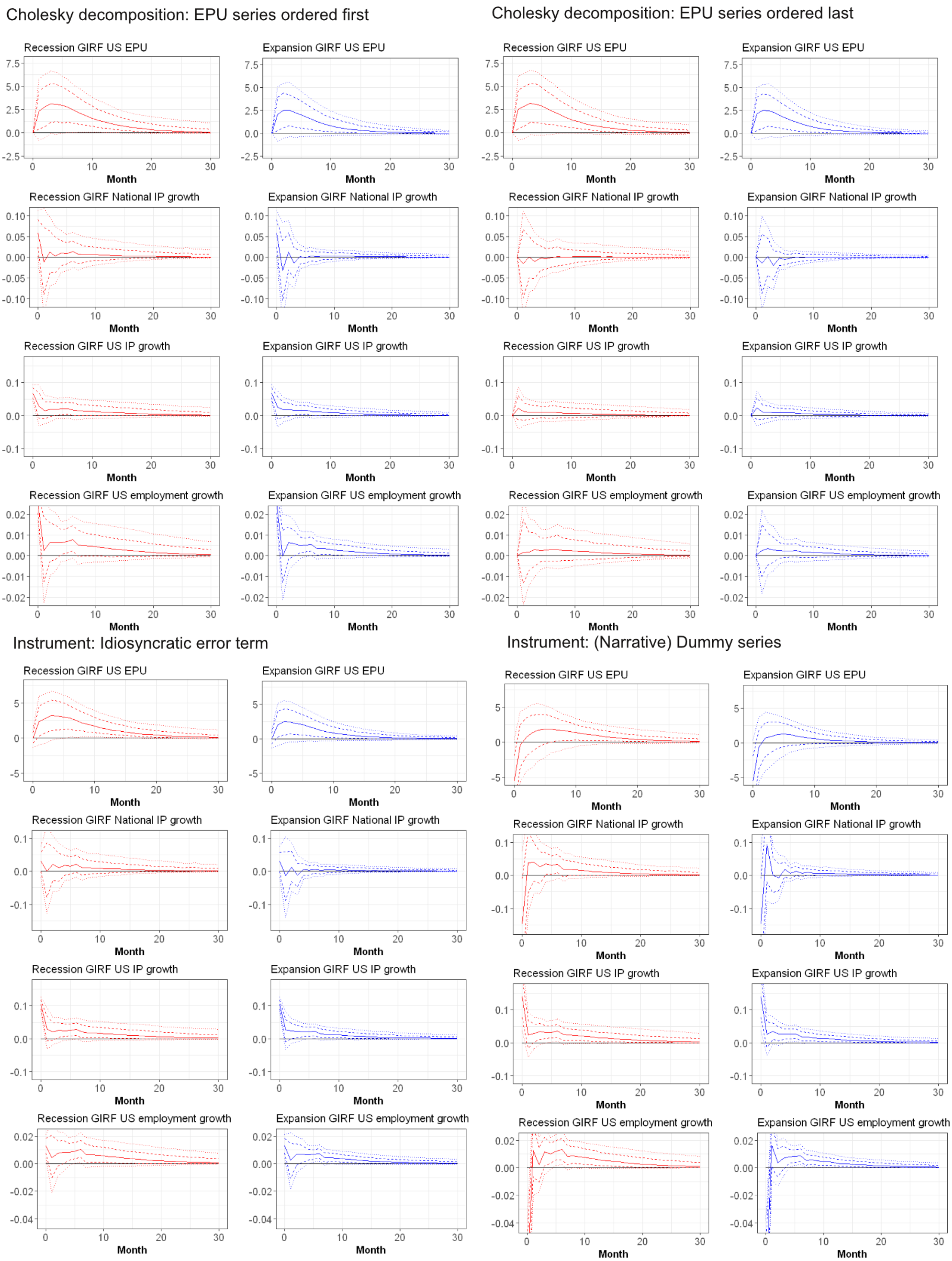


Figure E.5: Generalised impulse responses to a one-standard deviation shock to Italian EPU using different identification methods

This graph shows the responses of US EPU and the growth rate in IP and Employment to a one-standard deviation shock to Italian EPU (36.65 points). All growth rates were multiplied by 100 to allow for interpretation in percent. The impulse response functions in the top left corner use a Cholesky decomposition with Italian EPU ordered second after US EPU, the top right corner uses a Cholesky decomposition with US EPU and Italian EPU ordered last. The bottom row of impulse response functions uses external instruments for identification: the idiosyncratic error term from a dynamic factor model on the left side, and a dummy series on the right side. Parameters were estimated over the sample January 1997 to December 2015. The solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the simulated posterior distributions, and dotted lines represent the 5th and 95th percentile.

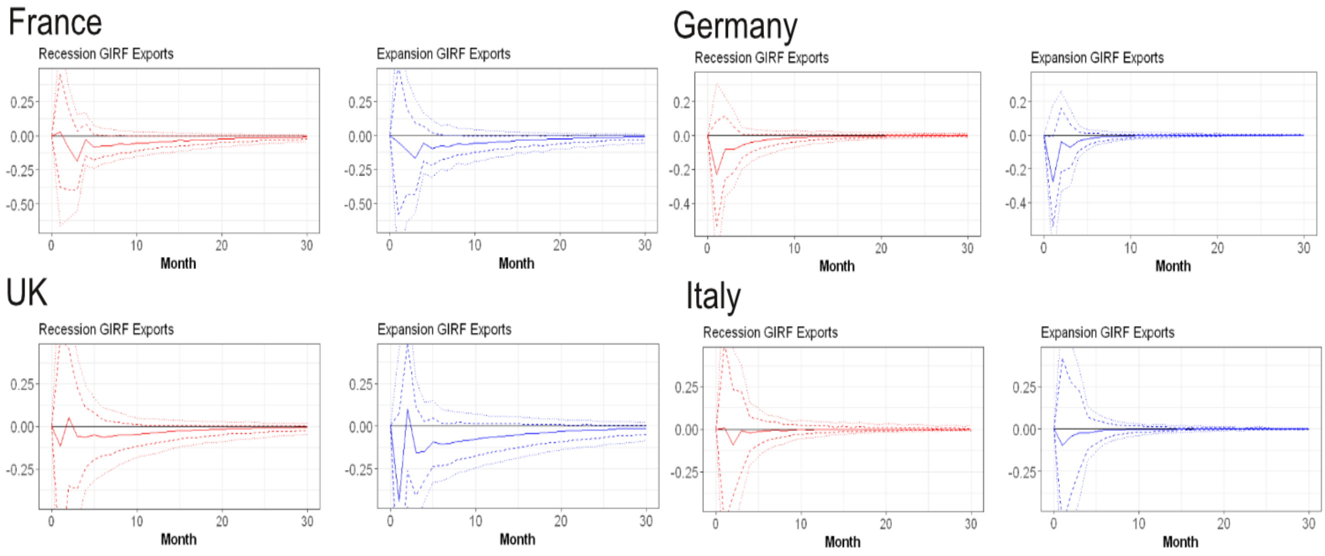


Figure E.6: Generalised impulse responses to a one-standard deviation shock to national EPU
This graph shows the responses of the growth rates of US exports to the respective countries to a one-standard deviation shock to the considered country's EPU. All growth rates were multiplied by 100 to allow for interpretation in percent. Identification of orthogonal shocks was achieved by using a Cholesky decomposition ordering US EPU and the European EPU series last. The solid line represents the posterior median, dashed lines represent the 16th and 84th percentile of the simulated posterior distributions, and dotted lines represent the 5th and 95th percentile.