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Economic Policy Uncertainty and Economic Activity: A Focus on Infrequent Structural Shifts

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Economic policy uncertainty and economic activity: a focus on infrequent structural shifts*

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Abstract

We provide new evidence on the role of economic policy uncertainty (EPU) in aggregate real economic activity in the US using a multiple-horizon Granger causality framework, while allowing for infrequent shifts in mean levels and growth rates of the system variables. Our empirical investigation shows that the predictive ability of EPU for economic activity significantly depends on the presence (or absence) of infrequent structural shifts and the absence from the information set of a forward looking variable such as the stock market level. We do not find economic policy uncertainty effects on industrial production once we control for stock prices irrespective of segmented trends removal. There is some evidence that EPU anticipates employment in the short-run, yet, after removing rare events, EPU does not anticipate employment at any horizon. In contrast, the stock market level is found to contain strong predictive direct and indirect information for economic activity that is robust to the presence of infrequent trend breaks.

Keywords: Economic policy uncertainty; real economic activity; Granger causality; Multi-horizon causality; Level shifts; Trend breaks; Vector autoregression

JEL-Code: E30, E32, C32

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1 Introduction

Economic policy uncertainty and its role in macroeconomic performance is intensely discussed in recent years, taking off after the work of Bloom (2009), and, especially, after the Great recession and throughout the subsequent "not-so-great" or slow recovery. Policy-related economic uncertainty is considered to be at historically high levels during these years both in the US and in Europe, while evidence arises that correlates increased policy uncertainty with the observed slow recovery of the US economy (Baker et al. 2012; Baker et al. 2013)

This paper aims in providing new evidence on the relationship or dynamic interaction between economic policy uncertainty and aggregate economic activity in the US by employing a multiple-horizon Granger causality testing procedure, as well as by focusing on the role of infrequent structural shifts and the role of omitted variables when estimating (popular) reduced form VAR models.

Bearing in mind that the notion of Granger causality is defined in terms of improved predictability[1] - providing information on whether a set of variables improves the forecasts of another set of variables - we examine the predictive ability of economic policy uncertainty for real economic activity, on the basis of the uncertainty index recently constructed by Baker et al. (2013), under (a) different trend treatments in the VAR model, when the time series employed appear to have stochastic and/or deterministic trends, the latter possibly presenting infrequent structural shifts, (b) the gradual adoption of higher-dimensional VAR models that include a monetary policy rate and a forward looking variable such as the stock market level in the information set and (c) different causality methods, with specific attention being paid on the distinction between the standard concept of Granger causality and the concept of multi-horizon causality developed by Dufour and Renault (1998) and empirically elaborated by Dufour et al. (2006).

The impact of uncertainty (but not necessarily economic policy uncertainty) on investment, employment, output or stock market performance has been examined in a considerable amount of studies in the literature. Bernanke (1983) points out that higher uncertainty regarding the status of the national economy and the investors' "fortune", along with investors' need for improved information, makes firms to postpone or delay investment and hiring, especially when

[1] More precisely, Granger causality refers to the predictability of a variable $X(t)$ from its own past, the past of another variable $Y(t)$, and possibly a vector $Z(t)$ of auxiliary variables, *one-step ahead.*

individual investment plans are irreversible, i.e. difficult to be "undone" once constructed. Rodrik (1991) and Hassett and Metcalf (1999) conclude negative effects of fiscal policy uncertainty on investment, while Bloom et al. (2007) provide evidence of weak responsiveness of firms to any given policy stimulus in periods of high uncertainty. The authors point out firms' caution in their employment responses due to the existence of labor hiring and firing costs. Further, Pástor and Veronesi (2012) provide a theoretical framework for the (negative) influence of government policy uncertainty on stock prices.

In terms of the empirical investigation of the effects of economic uncertainty on real aggregates, Alexopoulos and Cohen (2009) use two measures of uncertainty - a stock market volatility index and a newspaper based indicator- and find negative responses of economic activity (e.g. output, employment, consumption) to positive uncertainty shocks. Beetsma and Giuliodori (2013) find significant changes in the macroeconomic responses to stock market volatility shocks over time. Baker, Bloom and Davis (2013) find that positive innovations in economic policy uncertainty are followed by a decline in both industrial production and employment over several months after the uncertainty shock, implying potentially damaging economic effects of policy uncertainty. Bloom (2009) theoretical model suggests that the negative effects of uncertainty shocks on aggregate activity can be explained by the temporary pause in firms' investment and hiring. During periods of increased uncertainty, firms, especially those with high levels of dependence with government contracts, will postpone investment and hiring decisions until business conditions become clearer.

Further recent studies that examine the effects of uncertainty on economic activity include Leduc and Liu (2013a), Bachmann et al. (2013), Benati (2013), Jurado et al. (2014), Cesa-Bianchi et al. (2014). Leduc and Liu (2013a) find that uncertainty has macroeconomic effects by increasing unemployment and decreasing inflation, while these effects can be substantially amplified by search frictions in the labor market. Bachmann et al. (2013) construct a measure of business uncertainty and find little statistical or economic significance for the impact of uncertainty shocks to aggregate economic activity, which leads them to view uncertainty as an "epiphenomenon" rather than a "cause" of bad economic times. Jurado et al. (2014) also construct new macroeconomic uncertainty measures and find that important uncertainty episodes appear far more infrequently than indicated by popular uncertainty proxies, but when they do occur, they are larger, more persistent, and are more correlated with real activity. Benati (2013) employs a time-varying structural VAR approach and finds that the role of economic policy uncertainty in economic activity depends on the identification strategy for the uncertainty shocks, while Cesa-Bianchi et al. (2014) employ a global VAR to study the interrelationship between economic activity and volatility (uncertainty) and further assume that both these variables are driven by a similar set of common factors. The authors provide evidence of volatility being a symptom rather than a cause of economic instability. Finally, Nodari (2014) and Caggiano et al. (2014) examine the impact of uncertainty shocks (using financial regulation policy uncertainty and VIX, respectively)[2] on macroeconomic aggregates, particularly on unemployment dynamics, by employing non-linear (smooth transition) VAR models. The authors find strong asymmetric real effects of uncertainty shocks over the business cycle.

Most of the empirical literature employs structural VAR (SVAR) models as the main tool for dynamic or policy analysis and the identification of uncertainty shocks. The latter are usually identified with the use of the Cholesky approach, while the VAR model and, consequently, dynamic impulse responses are estimated under a standard benchmark treatment of trends, e.g. differencing, Hodrick-Prescott (HP) filtering or the inclusion of linear trends. Our aim in this paper is to extend both the design feature of how trends - the long run component - are treated and the impulse response analysis tool. In particular, we employ the Dufour and Renault (1998) multi-horizon causality concept[3] to investigate whether economic policy uncertainty helps to improve the forecasts of aggregate output and/or employment or alternatively, whether uncertainty regarding economic policy helps to anticipate economic activity. What is the ability of economic policy uncertainty to predict output and employment, and how can this ability be affected by the treatment of trends in the time series or the information set employed?[4]

We consider the concept of multiple horizon causality we employ to be very important when examining the dynamic interrelationships between a set of time series, since it can reveal additional information on multiple causal channels and the presence of causal chains among the system variables (Lütkepohl 1993, Dufour and Renault 1998, Hill 2007), except for the case of bivariate

[2] Chicago Board of Options and Exchange (CBOE) Market volatility index.

[3] The multi-horizon causality concept is considered to be a generalized notion of standard impulse response analysis, since the latter considers only a small subset of the coefficients of lagged variables in forecasts at greater horizons (Dufour and Renault 1998).

[4] Bearing in mind that economic policy uncertainty or stock market indices might be forward-looking variables that reflect future expectations of economic conditions, our interpretation of causal relations is strictly in terms of improved predictability.

VARs.[5] Multiple horizon or indirect causality might occur between two variables of direct interest at higher forecast horizons, revealing nuanced details on multiple-horizon causation which would be collapsed out when employing standard Granger causality test procedures. The Dufour et al. (2006) procedure we employ provides useful information on the time profile of causal effects, i.e. on the presence of causal delays, horizons at which causal effects take place and the direct or indirect nature of causal effects. Hence, in our empirical investigation we aim in providing new information on the causal channels between economic policy uncertainty and economic activity and on whether forecast horizon matters.

Regarding the presence of structural changes, taking them into account is important for two reasons. From a methodological point of view, Lütkepohl (1989) and Ng and Vogelsang (2002) show that Granger causality (GC) tests over-reject the null hypothesis of no Granger causality when mean shifts are present but are omitted from the VAR model (size issues). More precisely, Ng and Vogelsang (2002) show that the least square estimates of the VAR model are inconsistent when mean shifts are omitted, while, in general, a mean shift in any of the series will induce bias in all the VAR estimates.[6] The authors suggest that mean shifts should be taken into account in the VAR model, either by removing them from the data so that a VAR is formed for the demeaned data (two-step approach) or by adding the breaks directly to the VAR model (one-step approach). Moreover, the inclusion of breaks in the VAR model is also a matter of methodological consistency. If a structural break is present in a univariate series, then this break should also be present in the multivariate setting.

From an economic point of view, structural changes represent infrequent changes in economic fundamentals or changes to the general economic environ-

[5] The employment of high-dimensional VARs is important, since this additional information could remain hidden or lead to spurious correlations in a bivariate framework. Importantly, spurious correlations or hidden causal relationships need not only occur in a bivariate framework but also in a trivariate or even a multivariate framework that yet does not include all available auxiliary variables (See Hill 2007 and the author's discussion on the "compression" of information arising when auxiliary variables are omitted).

[6] The type of the mean shift can be of the additive outlier (AO) or the innovational outlier (IO) type, based on the terminology of Box and Tiao (1975). In our empirical analysis, the structural shifts are considered to be of the AO type. All the statistical procedures we employ to (a) assess trend function stability regardless of whether the noise component is stationary or having a unit root and then, (b) to test for unit roots in the noise component conditional on either the absence or presence of structural trend changes, are based on this type of structural shift approach. The additive outlier approach is widely used in many empirical studies as well.

ment (e.g. changes in fiscal or monetary conditions, labor market conditions etc.). These “big”, infrequent level shifts or trend breaks (i.e. average growth rate changes for series in logarithms) might induce a change in the level and/or the slope of the deterministic component of a time series, with segmented linear trends being produced in the latter case. Thus, authors often need to test whether, during the sample period under examination, there have been occurred “major events” or “shocks” which may have affected the trend function in a permanent way so that they can be modeled as a part of the deterministic trend component (Perron 1989; Campbell and Perron 1991). Modelling such rare infrequent shocks that lead to secular changes in mean levels and/or growth rates can have major implications both on estimation results and on the interpretation of dynamic interrelations. In what follows, we name trends, infrequently segmented trends and infrequently shifting mean levels as the secular component of the series, while the remaining "cyclical" component is termed non-secular and it might be stationary or having a driftless unit root representation.

Our empirical findings show that Granger causality results, at all horizons, significantly depend on the presence (or absence) of infrequent structural shifts in the time series employed and the absence of relevant variables from the information set. For example, after detrending, a reversal of Granger causality results between policy uncertainty and stock prices is observed, pointing to the power and size distorting effects of trend misspecification in reduced form VARs. Regarding the role of economic policy uncertainty in real economic activity, we find weak evidence of policy uncertainty effects on industrial production that disappear when we control for stock market levels (percentage deviation of stock market prices from their long run trend). This result is robust to the presence of infrequent trend breaks in the series. Further, prior to detrending, we find evidence that policy uncertainty affects employment in the short run (over a period of six months). After detrending, the transitory component of policy uncertainty has no effects on the detrended (non-secular) component of employment. Stock prices, in contrast, are found to contain strong direct and indirect predictive information for economic activity irrespective of trend treatment.

The paper is organized as follows: Section 2 describes the empirical investigation strategy, the data and the employed methodologies, while Section 3 presents our results. Section 4 provides additional evidence from orthogonal impulse response analysis, and some further robustness checking of the results is documented in Section 5. Finally, Section 6 concludes.

2 Empirical investigation

Our empirical investigation is based on the VAR model employed in Baker et al. (2013)[7] which, in its general form, consists of five variables, with the main interest being focused on the effects of US economic policy uncertainty on key aggregate economic activity variables such as output and/or employment. The Baker et al. (2013) VAR model further includes the S&P500 index and the effective federal funds rate to control for the stock market and interest rates, respectively.

The economic policy uncertainty (EPU) index we employ has been recently constructed by Baker et al. (2013),[8] and is considered as a measure (proxy) of movements in policy-related economic uncertainty over time. By construction, the EPU index might be related to uncertainty about fiscal, monetary or regulatory conditions.

More precisely, the US economic policy uncertainty index of Baker et al. (2013)[9] is considered to capture three underlying components of economic policy uncertainty. In brief, one component quantifies newspaper coverage of policy-related economic uncertainty, a second component reflects the number and revenue effects of federal tax code provisions set to expire in future years, and the third component captures the extent of disagreement among economic forecasters about policy relevant variables, e.g. future government purchases and future inflation.

Our empirical strategy is organized as follows: we start by testing for Granger causality between economic policy uncertainty and (the logarithm of) industrial production in a bivariate setting, which further allows for the presence of deterministic linear trends that the system variables, such as industrial production or employment, might present over time. Infrequent shifts are not considered in this first step. We then explore how the predictive ability of economic policy uncertainty for industrial production changes when additional variables that aim in controlling for important patterns within the economic system, such as the stock market or interest rates, are included.

The reasons for initially employing low-dimensional VAR models (2,3,4 variate models) rather than performing the analysis only with the 5-VAR model lies with our interest to identify the EPU effects by investigating the effects

[7] A similar VAR model has been also employed in Bloom (2009).

[8] Available on www.policyuncertainty.com

[9] The authors further construct economic policy uncerntainty indices for Canada and European countries.

of omitted variables in terms of spurious correlations or hidden causal effects among the system series, which, as mentioned above, occur when relevant information is omitted from the VAR model. For example, we are interested in examining whether economic policy uncertainty helps to anticipate output or employment in a bivariate or a trivariate setting, and, in turn, whether this predictability changes when we include a stock market price index, which is known as a forward looking variable and the relevant literature has shown to be strongly interrelated with economic activity.

The *2,3,4,5*-VAR models we sequentially employ provide substantial evidence on the presence of potential spurious relationships due to omitted variables, while the 5-VAR that includes (most of) the main interactions within the system (i.e. stock market, prices/interest rates, real aggregates) is considered to provide a more complete picture on causal relations. Granger causality analysis is conducted in both the Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) fashion, as well as the Dufour et al. (2006) causality testing at different horizons, so that we can have further information on the presence (or absence) of indirect causal chains, causation delays and short-run or long-run causality. Since the Dufour et al. (2006) procedure is described in detail in the original paper,[10] and in order to conserve space, details on the procedure may be found in Appendix B.

As a next step, we take into account the presence of structural shifts in the level and/or the slope of the deterministic component of the system variables. Do industrial production, employment or economic policy uncertainty present structural changes which are related to infrequent changes, e.g. in fiscal, monetary, labor market conditions or in productivity, and should be modeled as part of the deterministic component? Does non-modeling of such secular shifts affect the predictive ability of the system variables?

In our analysis, we employ recent techniques that test for shifts in the trend function of univariate time series and are robust regardless of whether the noise component is stationary or having a unit root. In order to test for Granger causality, we employ the two-step procedure for estimating the VAR models. Thus, we first estimate the structural breaks, and then we estimate the VAR model for the demeaned or detrended data. Our analysis further offers a comparison of the Granger causality results with the impulse response results obtained in Baker et al. (2013) and also with other recent studies in the relevant

[10] In addition, a recent application of the Dufour et al. (2006) procedure may be found in Salamaliki, Venetis and Giannakopoulos (2013).

literature.

2.1 Data and variables employed

The time series we employ in our empirical VAR model correspond to the economic policy uncertainty (EPU) index constructed by Baker et al. (2013), log(industrial production), log(employment), log(S&P500) and the effective federal funds rate (effr). Information on data sources may be found in Appendix A. The sample spans the period 1985m1-2013m8 and consists of 344 monthly observations. Figure 1 below presents the variables along with the estimated in-sample long-run level (mean, linear trend or segmented trend) whose specification and estimation is explained in the next subsection and in Appendix C.

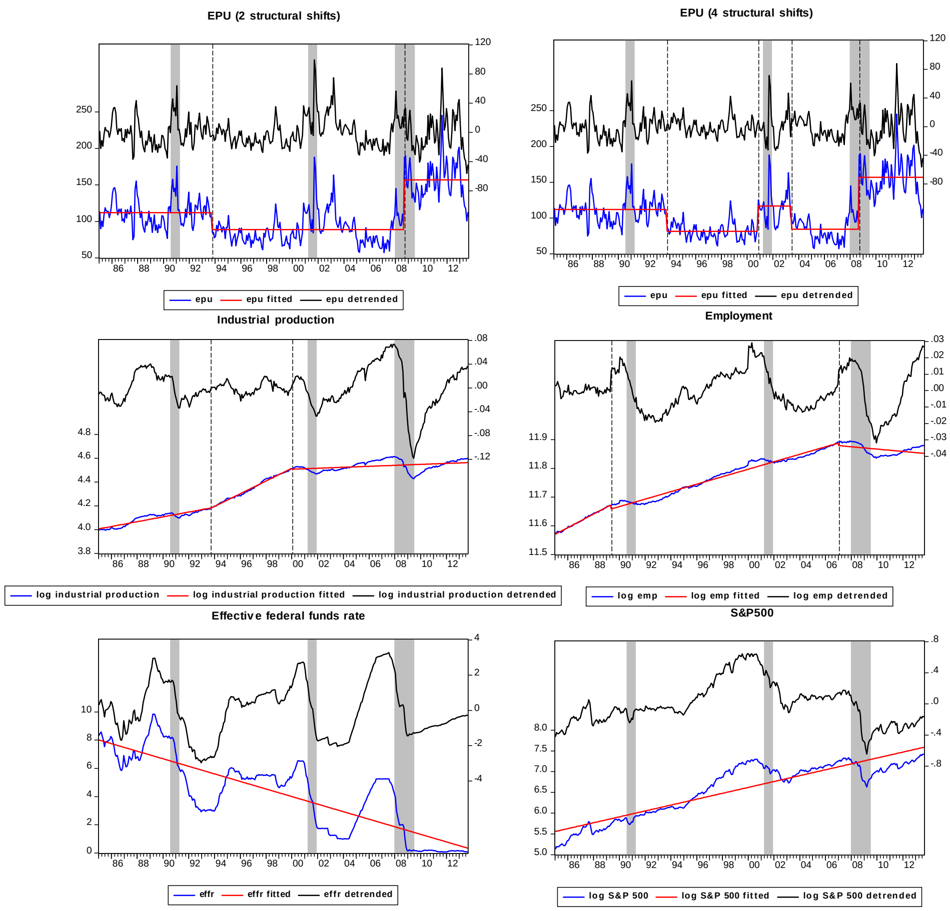

Fig 1. VAR system variables, fitted (segmented or linear) trends and detrended components. Panels (from left to right) show: (a) EPU with two level shifts, (b) EPU with four level shifts, (c) log industrial production with fitted segmented trend, (d) log employment with fitted segmented trend, (e) effective federal funds rate (effr), and linear trend (f) log S&P500 and linear trend. Estimated break points are shown as vertical dashed lines. U.S. recession periods are marked by shaded areas. The fitted trend function is obtained by regressing the series on a constant and intercept shift dummies or on a constant, a trend, an intercept shift dummy and a slope shift dummy.

2.2 Testing for structural shifts

2.2.1 Industrial production and employment

In order to test for infrequent structural trend shifts in univariate time series, when the break dates are unknown, we employ the recent procedures suggested by Perron and Yabu (2009, henceforth PY), Harvey et al. (2009, henceforth HLTa) and Kejriwal and Perron (2010, henceforth KP). These procedures are robust to the presence or not of a unit root in the underlying error process and avoid the "circular testing problem" that often arises in empirical applications between tests on the parameters of the trend function and unit root tests. Thus, no a priori information regarding the order of integration of the time series is needed. The most general univariate model we considered is described by

$$y_t = \mu_0 + \beta_0 t + \sum_{i=1}^{m} \mu_i DU_{it} + \sum_{i=1}^{m} \beta_i DT_{it} + u_t \quad (1)$$

$$u_t = \alpha u_{t-1} + v_t \quad (2)$$

where $DU_{it} = \mathbf{1}(t > T_i)$ and $DT_{it} = (t - T_i)\,\mathbf{1}(t > T_i)$ are level and trend shift dummies for $i = 1, ..., m$ with m the number of breaks and $\mathbf{1}(\cdot)$ the indicator function. The breaks in trend occur at points $T_i = [T\lambda_i]$ with fractions $0 < \lambda_1 < \lambda_2 < ... < \lambda_m < 1$. The underlying error process u_t is either $I(0)$ when $|\alpha| < 1$ or $I(1)$ when $\alpha = 1$ while v_t is a mean zero stationary short memory process. This is the local disjoint broken trend model of Perron and Zhu (2005) that allows for simultaneous changes in the level and slope or the joint broken trend model if $\mu_i = 0$ for $i = 1, ..., m$. The maximum number of breaks is set equal to $m = 2$ for reasons explained in Appendix C.

The first stage of our testing procedure involves the use of PY, HLTa and KP tests for robust detection of breaks in the level and slope of the trend function and robust estimation of the number of breaks, if present. Then, in the latter case, we proceed with robust estimation of the break locations as outlined in Carrion-i-Silvestre et al. (2009, henceforth CKP).[11] Finally, we apply powerful unit root tests that allow for structural breaks under both the null and alternative hypotheses proposed by CKP and Harvey et al. (2013, henceforth HLTb). The HLTb test is applied only to the joint broken trend model and has superior power properties for magnitudes of trend breaks typically observed in practice. In order to conserve space, details on the procedures adopted and a

[11] Carrion-i-Silvestre et al. (2009, p. 1767, Section 5.1)

table with estimation results (table C1) can be found in Appendix C.

In summary, the aforementioned procedures are applied to the log-industrial production and log-employment series and a summary of the results appears in Table 1. Both series are presented in Figure 1 where it seems clear that at least one major shift in the slope or level and slope of the trend function is present. Although visual inspection is revealing, the testing procedure provides strong evidence of two breaks in the trend of log-industrial production and log-employment.

The industrial production breaks located at 1993m08 and 1999m12, essentially mark the expansionary period of the 1990s. The differences in the estimated average growth rates over each segment are significant and point to a large increase in the annual growth rate from 2.02% in the 1985m1 - 1993m8 segment to 5.34% in the 1993m9 - 1999m12 segment and a significant slowdown with an annual growth rate of 0.40% in the last segment 2000m1 - 2013m8. Similar important changes are observed in employment growth rates after the estimated break dates, 1989m04 and 2006m10, yet the change in growth rates is monotonic with two consecutive reductions in employment growth. Again, the break dates are located in expansionary periods however both are now located "shortly" before two recession periods (1990m07 - 1991m03 and 2007m12 - 2009m06). A persistent decline of the average employment growth rate is observed after the first trend break where the average growth rate drops from an annual rate of 2.36% prior to 1989m4 to 1.30% after the first break and up to 2006m10. The second break - that originates almost a year before the financial crisis is realized - implies a drop to a negative employment growth rate from 1.30% to -0.40% annually.

These growth rate changes have not gone unnoticed in the literature. The dramatic surge of industrial production growth in the 1990's coincides with the remarkable U.S economy performance in that period (see e.g. Oliner and Sichel 2000, Jorgenson et al. 2008). The high-tech revolution is the dominant candidate underlying cause, with information technology shocks leading to a permanent improvement in growth prospects (Jorgenson 2001). Regarding employment, the slowdown in employment growth rates, at least since the 1990s, is documented, inter alia, in Clark and Nakata (2006) and Stock and Watson (2012) and it can be attributed to a fall in population growth and less rapid increases in labor force participation. Importantly, even when we allow for two trend breaks, the noise component in both series appears to have a unit root.

2.2.2 Economic policy uncertainty

With respect to the economic policy uncertainty index, EPU, a different detrending procedure is adopted. The index proxies for movements in policy-related economic uncertainty over time and resembles a monthly volatility series. Indeed, Baker et al. (2013) find a correlation coefficient of 0.578 between EPU and the VIX index.[12] As such, we assume that the EPU series is inherently non-trending and does not conform with either deterministic trends or stochastic trends. Indeed, visual inspection of the time series graph in Figure 5 hints towards stationarity along with the existence of level shifts, where sudden movements in the long run level of the index persist through time for several years (more than the typical business cycles duration[13]). Level shifts confound the estimation of persistence and can have adverse effects on causality tests.

Preliminary statistical analysis (Figure C1, Appendix C) shows a slow decay for the autocorrelation function of the EPU series with a "plateau" at lags 7 to 11. An $AR(p)$ model fitting procedure using the AIC criterion and assuming stationarity produced an optimal lag length of $p = 4$ with the sum of autoregressive coefficients equal to 0.8965, while the BIC criterion selects $p = 1$ with autoregressive coefficient 0.8521. In addition, a large number of unit root tests (Appendix C, Table C2) rejects the null hypothesis of a unit root (stochastic trend) in the EPU series. As such, we use the sequential procedure of Bai (1997) and Bai and Perron (1998, 2003), as well as information criteria methods to estimate the number and location of level shifts prior to demeaning. Details on the tests for structural shifts employed may be found in Appendix C.

In summary, the Bai (1997), Bai and Perron, (1998, 2003) sequential methods identify two breaks (a decrease and a subsequent increase in policy uncertainty mean levels), while information criteria and in particular the corrected information criteria proposed by Hall et al. (2013) identify two additional breaks in the series that imply an almost three years period of increased policy uncertainty in the late 2000 to mid 2003 period. The differences in the estimated means over each segment are significant and point to a decrease of 27% after 1993m9, an increase of 43% after 2000m10, another decrease of 27% after 2003m5 and a large increase of 85% after 2008m8.

The first structural shift in economic policy uncertainty that occurs during

[12] VIX index of 30-day implied volatility on the S&P500 index, provided by the Chicago Board of Options and Exchange (CBOE).

[13] The NBER (`http://www.nber.org/cycles/cyclesmain.html`) average Peak-to-Trough duration for the 1945 - 2009 period is 11.1 months.

1993 indicates a decrease in policy uncertainty just after the Clinton tax reforms and signifies a long period of low policy uncertainty that coincides with the prolong economic expansion during the period 1992-2000. The last structural shift occurs during 2008, implying a large increase in policy uncertainty related to the recent financial crisis of 2007-2009 that settles after the Lehman bankruptcy. The other two level shifts found when we adopt additional information criteria methods correspond to an increase in policy uncertainty in late 2000 and a subsequent decrease during 2003. This non-monotonic shift of increased policy uncertainty begins around the time of the dotcom collapse and the first G.W. Bush presidential elections and covers the 2001 recession, the 9/11 attacks, the stock-market scandals of early 2002 (WorldCom, Enron etc), while it "settles" two months after the onset of Gulf War II. For reasons of comparison, our analysis of Granger causality testing in the presence of infrequent structural shifts is thus conducted under both cases of two and four level shifts in economic policy uncertainty.

Finally, the (logarithm of) S&P500 index and the effective federal funds rate are not considered to present "infrequent" structural trend breaks. The log(S&P500) series follows a random walk with drift implying a long-run trend component in S&P500 that is not necessarily linear rather than exponential, while deviations of stock index returns from their mean are unforecastable. The geometric random walk model for the stock index levels is in accordance with standard present value models that assume a geometric random walk of dividends. The (positive) drift term represents the continuously compounded expected rate of return of investment in S&P500, while the logarithms stabilize the variance of the first differences of the index and linearize the exponential type growth in the original series.

With respect to the, directly controlled by the Federal Open Market Committee (FOMC), effective federal funds rate, we keep with a large number of studies that have previously examined the unit root behavior of interest rates and support the stylized fact that interest rates are $I\,(1)$ processes, see Stock and Watson (1988, p. 1106 and 1999, p.54) and Sarno and Thornton (2003), among others. Indeed, a number of unit root tests that we conduct suggest that the effective federal funds rate is $I(1)$. Hence, although a number of nonlinearities and persistent shifts can be observed in the series, we do not characterize them as "infrequent" but rather as stemming from the series distribution.

Insert Table 1 about here

[Table 1.Summary results for deterministic component breaks and unit root tests]

3 Empirical results

3.1 Deterministic trend treatment: linear trend

We first focus on the causality results that arise under the benchmark trend treatment, i.e. when a standard linear trend is included in the VAR model. Table 2 presents the results based on the Toda and Yamamoto (1995) approach, while Tables 3a, 3b present multi-horizon causality results based on the Dufour et al. (2006) approach.[14] The VAR lag order p for each model and each trend treatment case is shown in Table D1 of Appendix D. The maximum horizon length, h, for each VAR model is based on the $m_3 \times p+1$ rule provided by Dufour and Renault (1998), where m_3 refers to the number of the system auxiliary variables and p the number of VAR lags.[15]

Table 2 shows that economic policy uncertainty helps to anticipate industrial production both in the bivariate setting and, sequentially, when we add employment and the effective federal funds rate in the VAR model (2-VAR, 3-VAR and 4-VAR). Based on this approach, this causal effect is of direct nature, occurring at forecast horizon one. However, when we include S&P500 - as an attempt to control for the stock market which is known to be associated with economic activity variables (see e.g. the early studies of Blanchard 1981, Fama 1990) - the predictive ability of economic policy uncertainty for industrial production is eliminated. The causality effects that appear in the 2-variate, 3-variate or the 4-variate settings might thus be considered as spurious correlations due to the absence of a relevant variable, i.e. the stock market index, which yet appears to contain useful predictive information for both industrial production (and employment) and economic policy uncertainty. Of course, the forward looking character of the stock market prevents from claims of strict causality identification although recent studies (e.g. Bond et al. 2012) point to the real effects of financial markets predominantly through the informational

[14]For space reasons, we do not present tables with simulated p-values of the multi-horizon causality tests and/or the statistics themselves. We rather report significant horizons at which the null hypothesis of non-causality is rejected at the 5% and 10% significance levels. Detailed tables are available upon request.

[15]Dufour and Renault (1998) show that non-causality up to horizon $m_3 \times p + 1$ is sufficient for non-causality at all horizons. The number of auxiliary variables equals the number of system variables (2, 3, 4 or 5) minus 2, since the GC tests involve two variables in every case.

role of market prices.

Insert Table 2 about here

[Table 2. Toda-Yamamoto causality results - standard linear trend included]

These results remain valid when the Dufour et al. (2006) approach is used. For the 3- and 4-variable VAR, we find that economic policy uncertainty helps to anticipate industrial production over the first five months (at horizons 1 to 5), yet this causal relationship is eliminated (at all horizons) once the stock market variable is included in the model. Again, both economic policy uncertainty and industrial production respond to changes in log(S&P500), while the causal effect of log(S&P500) to the two variables appears to be of direct nature, i.e. it occurs at horizon 1, and it takes place over the next 7 months and 13 months (hence, at all horizons) for economic policy uncertainty and industrial production, respectively.

Insert Table 3a about here

[Table 3a. 3 - 4 VAR DPR causality results - standard linear trend included]

Insert Table 3b about here

[Table 3b. 5 - VAR DPR causality results - standard linear trend included]

The latter result can be considered as an example of what is referred to in Hill (2007) as "compression of information" when auxiliary variables are available, yet they are omitted from the model. More precisely, compression of information may arise when Y causes X within the truncated system but does not cause X within the complete system. Causality within the truncated system (i.e. the 2-VAR, 3-VAR or 4-VAR model) may be observed due to the contemporaneous association of Y (economic policy uncertainty) with an omitted auxiliary variable Z (log-S&P500), that causes X (industrial production). Once we include Z in the information set, no causal relationship between Y and X is observed.[16] Indeed, reduced form errors from the economic policy uncertainty equation and log(S&P500) index equation in the 5-VAR model are contemporaneously correlated (correlation is estimated to be -0.37), while a

[16] A second case of compression of information might also arise when non-causation from variable Y to X is observed within the truncated system (Y, X, Z_1) while we find causation within the complete system (Y, X, Z_1, Z_2); due to the compressed causal chains linked by the omitted auxiliary variables Z_2.

test of instantaneous causality strongly rejects the null hypothesis of no contemporaneous correlation.[17]

In contrast, our results indicate that economic policy uncertainty does cause employment in the 3-VAR, 4-VAR and 5-VAR models. Thus, while industrial production does not appear to respond directly or indirectly to economic policy uncertainty changes, the other variable that represents economic activity (employment) is found to respond to such shocks (even though we have corrected for a proportion of the EPU forward looking component when we control for stock market deviations from its long run path). The connection of high levels of EPU and the slow recovery in the US labor market after the great recession through the firms' reluctance to hire when EPU is increased is uncovered in Leduc and Liu (2013b). However, our results also suggest a (direct) causal feedback from employment to economic policy uncertainty ($h = 1, 7-8$), implying that changes in employment contain predictive information for policy uncertainty.

Interestingly, economic policy uncertainty anticipates the effective federal funds rate at all horizons in both the 4-VAR ($h = 1-5$) and 5-VAR ($h = 1-13$). This sensitivity of (policy) interest rate to changes in economic uncertainty is also documented by Bekaert et al. (2013) who find that the VIX index strongly co-moves with measures of the monetary policy stance and in Nodari (2014) who finds that financial regulation policy uncertainty is quantitatively relevant for movements in the federal funds rate. Moreover, a causal feedback (bidirectional causality) is observed from industrial production to log(S&P500) (at $h = 1, 2$), while industrial production further includes predictive information for employment ($h = 1 - 7$) and the effective federal funds rate ($h = 1$). The effective federal funds rate does not appear to contain predictive content for any of the system variables.

Regarding the possibility of indirect causal effects, there is evidence of a causal chain and transmitted predictive information for the case of S&P500, which appears to anticipate employment with a delay at long horizons $h = 10$ to 13, i.e. at least after 10 months. This indirect causality might emerge due to a causal chain through industrial production, i.e. a chain that involves, at least at horizon 1, the effect of S&P500 on industrial production, and the effect of industrial production on employment. Another causal chain might

[17] Pástor and Veronesi (2012) show that stock market returns at the announcements of policy changes should be negative unless previous policy was perceived as harmful. Negative correlation of the stock market growth with the economic policy uncertainty index is also documented by Benati (2013).

be perceived through policy uncertainty (effect of S&P500 on economic policy uncertainty, effect of economic policy uncertainty on employment).[18] All other causal relations appear to be of direct nature, occurring at horizon 1, although we observe differences in the duration of causal effects. For example, industrial production causes log(S&P500) at horizons 1-2, employment over the first seven months and the effective federal funds rate at both short-run and long-run horizons.

Our results thus provide substantial evidence on the possibility of spurious or overstated policy effects due to omitted variables and in particular the stock market performance variable, while the 5-VAR that includes (most of) the main interactions within the system (i.e. stock market, prices/interest rates, real aggregates) is concluded to provide a more complete and clear picture on causal relations.

The importance for including a stock market variable in the VAR model when examining responses of economic activity variables is in agreement with the relevant literature, in which strong interactions between the stock market and economic activity have been established (see, inter alia, Blanchard 1981, Huang and Kracaw 1984, Fama 1990, Canova and De Nicolo 1995, Choi et al. 1999, Croux and Reusens 2013). In addition, the inclusion of the stock market index is also important for understanding the effects of economic uncertainty, since reduced-form shocks to both variables are shown to be significantly negatively correlated.[19]

3.2 Deterministic trend treatment: structural shifts in linear trend

We now turn to the second case of trend treatment, which is the case that takes into account the presence of infrequent structural shifts in the deterministic component of the univariate time series. Thus, we eliminate very low frequency variation from the series that corresponds to the secular slow down in employ-

[18] However, as it will be explained in the next subsection, the first causal chain through industrial production is the more likely to be observed.

[19] On the other hand, if we had first employed e.g. a trivariate VAR consisting of economic policy uncertainty, industrial production and the stock market variable, we would not find any causal relationship between the first two variables (results are not reported), since in that case the omitted variable problem would be eliminated. However, we would still might have missing information on potential causal links and indirect causal relations among the system variables, which in contrast can be revealed when using multi-horizon causality methods.

ment trend growth over two instances in our post 1985 sample, two incidents of secular change in industrial production growth, one positive during the 1990s and one negative after 2000 and two or four incidents of permanent (prolonged) changes in the mean level of economic uncertainty. In the following analysis, the "cyclical" component of the series stands for non-secular movements and it is not necessarily synonymous with stationarity (as seen by the assumptions in (1) and (2)). The results indicate that the inclusion of a few breaks in the deterministic component can affect significantly causality test outcomes in both directions: some causality effects are eliminated while new causal links now appear among some pairs of variables. Tables 4, 5a,5b present the Toda-Yamamoto (1995) and Dufour et al. (2006) causality results, respectively while it is particularly interesting to compare the results of tables 3b, 5b (and 7b later on).

Insert Table 4 about here

[Table 4. Toda-Yamamoto causality results - structural shifts in linear trend included - 2 level shifts in EPU]

Insert Table 5a about here

[Table 5a. 3 - 4 VAR DPR causality results - structural shifts in linear trend included - 2 level shifts in EPU]

Insert Table 5b about here

[Table 5b. 5 -VAR DPR causality results - structural shifts in linear trend included - 2 level shifts in EPU]

Regarding the economic policy uncertainty index and its predictive ability on industrial production, the same linkage appears as in the standard case, i.e. economic policy uncertainty helps to predict industrial production in the 2-VAR, 3-VAR and 4-VAR settings, however, prediction improvement is eliminated when the stock market variable is included in the model. The log(S&P500) stock price index is found again to anticipate both economic policy uncertainty and industrial production, albeit causality horizon lengths have been diminished to $h = 1-3$ for economic policy uncertainty and $h = 1-7$ for industrial production. Thus, mistreatment of trends by ignoring infrequent secular changes can magnify, at least the duration, of causal relations. Nonetheless, in the case of the economic policy uncertainty - industrial production relationship, what appears to be important is the inclusion of the stock market variable (that eliminates causal effects from economic uncertainty to industrial production observed in the 3-variate or 4-variate settings). EPU aggregate effects on real economic activity might indeed reflect forward looking behavior embodying expectations or forecasts as to where the economy is headed.

An important difference is however observed in the economic policy uncertainty - employment relationship. The causal effects of economic policy uncertainty on employment are eliminated once two structural shifts in both variables are taken into account, since economic policy uncertainty does not appear to contain predictive information for employment in any of the 3-VAR, 4-VAR or 5-VAR models. Therefore, it is a few permanent and large changes in the secular level of EPU and employment growth that account for the previously found dynamic relation of those two series. This result, along with the fact that again the S&P500 price index helps to anticipate both industrial production and employment, points to the fact that economic policy uncertainty does not affect directly or indirectly- in the Granger causality sense - "cyclical" aggregate economic activity. On the contrary, it is the stock market performance which appears to contain predictive information for "cyclical" economic activity. In addition, the direct causal feedback from employment to policy uncertainty is eliminated as well.[20] Some indirect causal effects from employment to economic policy uncertainty are observed at horizons 8-9, 11-12, yet a causal chain through the system variables cannot be established, as (cyclical) employment does not anticipate any other variable in the system.

The S&P500 price index has still been found to anticipate employment, yet the causal delay now appears to be shorter. More precisely, we find that S&P500 helps to predict employment at horizons 1-2 and 4-13. Given that rejection of non-causality at $h = 1$ has a marginal p-value of 0.0905, we might conclude indirect causality between the two variables, as it was previously observed. Notice, however, that in this case the only observed causal chain occurs through industrial production, i.e. the effect of S&P500 to industrial production, and the effect of industrial production on employment. The causal chain through economic policy uncertainty is no longer observed. Rather, we have a broken causal chain due to the fact that S&P500 affects policy uncertainty, yet the effect of policy uncertainty on employment is eliminated once structural shifts are considered.

[20] This result is more evident when employing the Toda-Yamamoto procedure (results in Table 4 or 6). In addition, this finding can be attributed to the fact that both employment growth changes happen in advance of the first and last mean level shifts in EPU, the latter being dramatically large as it coincides with the deepening of the financial crisis on September 2008. It appears that such a coincidence can alter GC results by affecting the power of the tests through the introduction of additional non-stationarity that spuriously "correlates" within sample.

In addition, the causal effects of economic policy uncertainty on the effective federal funds rate (at all horizons), and industrial production effects on S&P500 (now occurring at all horizons), the effective federal funds rate ($h = 1, 6-9, 12-13$), and employment ($h = 1-6$) are still present. Interestingly, industrial production now appears to contain predictive information for economic policy uncertainty. This causal effect appears to be indirect and involves the effect of industrial production on S&P500, and the effect of S&P500 on economic policy uncertainty.

When four structural shifts in economic policy uncertainty are considered, the results shown in Tables 6, 7a,7b regarding the predictive ability of economic policy uncertainty to industrial production and employment do not differ when compared to the 2-structural shifts case. In addition, the indirect causality from S&P500 to employment is reinforced. S&P500 predicts employment indirectly (at $h = 2, 4-13$), through industrial production, and industrial production directly over all 13 months. Industrial production has still been found to contain predictive information for all the system variables.

Insert Table 6 about here

[Table 6. Toda-Yamamoto causality results - structural shifts in linear trend included - 4 level shifts in EPU]

Insert Table 7a about here

[Table 7a. 3 - 4 VAR DPR causality results - structural shifts in linear trend included - 4 level shifts in EPU]

Insert Table 7b about here

[Table 7b. 5 - VAR DPR causality results - structural shifts in linear trend included - 4 level shifts in EPU]

There are some differences however that need further discussion. The introduction of at least two level shifts in EPU generates a GC reversal. For example, although in the standard case we did not find evidence of causal effects from economic policy uncertainty to the stock price index, the former variable is now found to contain predictive information for S&P500 over several months ahead, at $h = 1-8$, under either two or four EPU level shifts.[21] On the other hand, the predictive content of S&P500 for economic policy uncertainty appears to gradually diminish when moving from the standard detrending case to the 2- and 4-

[21] Interestingly, a similar result holds for the case of causal effects from the effective federal funds rate to S&P500. After the removal of breaks from EPU, industrial production and employment, the federal funds rate predict movements in the percentage deviation of S&P500 from its long run trend over all horizons.

level shifts cases (causal effects from S&P500 to economic policy uncertainty are observed at horizons 1-7, 1-3 and at none horizon for each case, respectively).

The former, with the direction of causality now running from EPU to S&P500, could be attributed to distorting variance effects when large level shifts are left unaccounted. For example, in the two breaks case (involves the first and last in-sample breaks), the level shift dummies exogenously account for 57% of the variation in EPU. Hence, shocks to the transitory component of EPU might anticipate adverse movements in the stock market, but this effect can be masked by discrepancies in the timing of large secular movements in the series. For example, log(S&P500) (percentage deviation from linear trend) begins a deep downward movement below its long run trend several months before the last large level increase in EPU. The latter effect, that is the vanishing influence of S&P500 on EPU, can be a manifestation of size distortions in GC tests when structural shifts are omitted.

Summing up our findings, regarding the causal relationship between economic policy uncertainty and the first variable representing real economic activity, i.e. industrial production, the results appear to be robust across all VAR specifications. In all cases (standard linear trend, 2-structural shifts, 4-structural shifts case) the 2-VAR, 3-VAR and 4-VAR models suggest that economic policy uncertainty contains predictive information for industrial production, while the 5-VAR models that further include the stock market performance variable point to the opposite conclusion: economic policy uncertainty does not help to anticipate aggregate industrial production. In contrast, it is the S&P500 stock price index, which is negatively contemporaneously associated with economic policy uncertainty, that seems to contain predictive information for both industrial production (directly) and employment (indirectly, through industrial production). The latter result further implies that the S&P500 stock market index is a relevant variable that should not be excluded from the information set when the relationship between economic policy uncertainty and real economic activity is examined.

With respect to employment, the results suggest no predictive content from economic policy uncertainty in all the 3-VAR, 4-VAR and 5-VAR models, once structural shifts are taken into account, or alternatively, the predictive ability of economic policy uncertainty for employment is identified only when secular changes are left unaccounted. Finally, the level of industrial production appears to provide significant predictive information for all system variables (expect for EPU in the standard case), while, importantly, this predictive ability is not eliminated with the inclusion of structural shifts.

4 Evidence from impulse response analysis

In this section, we perform a benchmark impulse response analysis based on our empirical 5-VAR models and we discuss the potential additional information that can be provided when using multi-horizon Granger causality methods (and appropriate infrequent shifts removal). Impulse responses have proved to be a convenient method of summarizing the dynamic relationships among variables, particularly for policy analysis reasons.[22] In all cases below, response standard errors are computed with Monte Carlo simulation methods (1000 repetitions).[23]

Figures 2 - 8 present selected impulse response functions, with the dashed (red) outer lines being the ± 2 times standard-error bands. The figures show the estimated dynamic responses of 100 times the log-industrial production and 100 times the log-employment to a positive, one-standard-deviation shock to either the EPU or to 100 times the log-S&P500. The first case is interpreted as an unanticipated increase of economic policy uncertainty while the second as an unanticipated increase in stock market levels. The responses can be interpreted as percentages of baseline levels.

We first estimate the response of industrial production and employment to economic policy uncertainty shocks using the same ordering as in the study of Baker et al. (2013) to identify orthogonal shocks. According to this Cholesky ordering, economic policy uncertainty is positioned first permitting the least response of this variable to the remaining four, while industrial production is positioned last permitting the greatest possible response of this variable to the remaining four (case 1 below).[24] Then, we reverse the ordering of the first

[22] Impulse-response functions from non-stationary VAR in levels are consistently estimated except for long-run horizons where the estimated impulse responses tend to random variables rather than the true impulse responses as the sample size increases (Phillips, 1998). Hence, for short- to medium-run horizons, estimated impulse responses from nonstationary VAR in levels models can be reliable. As such, we follow a large number of studies that employ this estimation approach. In addition, our interest lies in comparing impulses with causality results from the Toda-Yamamoto (1995) procedure that avoids pre-testing for cointegration.

[23] Kilian (1998) provides a bias-corrected bootstrap method that can be more accurate in small samples than standard delta method approximations to asymptotic intervals, standard bootstrap intervals or Monte Carlo integration intervals as the ones we use. However, our interest lies not on exact inference for the impulses rather to exemplify major patterns (periods to maximum response and return to near zero levels).

[24] Other studies that include uncertainty measures first in the VAR model include Alexopoulos and Cohen (2009) and Bachmann et al. (2013).

two variables, hence we put the stock market index first followed by economic policy uncertainty. In both cases, the macroeconomic real activity variables are positioned after economic policy uncertainty and the stock market index. We summarize the results of the first two cases below:

Case 1: 5-VAR model, Cholesky ordering: EPU, S&P500, effective federal funds rate, employment, industrial production, 4 lags, monthly linear trend. The response of industrial production to a one standard deviation shock in economic policy uncertainty is small and statistically insignificant on and near impact, followed by a period of statistically significant reductions for the period 2-14 months[25] with the peak negative impact being -0.41% at 9 months.[26] The estimated impulse response turns to insignificant at $h = 15$, implying insignificance of any rebound in industrial production. In addition, the response of employment is also insignificant on and near impact, followed by a period of statistically significant reductions for the period 4-19 months bottoming out at 11 months with the peak negative impact being -0.15%. Again, any rebound is found to be statistically insignificant as 20 months after the EPU shock, employment is back to trend. On the other hand, the responses of industrial production and employment to a one standard deviation shock in S&P500 appear to be significant after 3 and 8 months, respectively.

[25] Reported months correspond to horizons 3-15 in the impulse responses graph 6. The same rule applies to all reported months in all impulse response cases.

[26] This corresponds to the estimated peak negative impact of -2.5% reported in Baker et al. (2013), who consider a 102 point innovation in policy uncertainty. However, the peak in this case is estimated at 14 months.

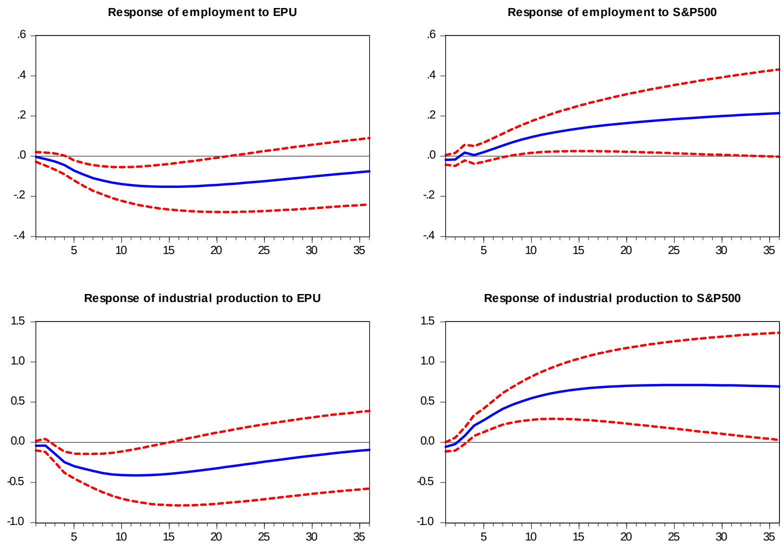

Fig. 2. Impulse response functions, case 1.

Case 2: 5-VAR model, Cholesky ordering: S&P500, EPU , effective federal funds rate, employment, industrial production, 4 lags, monthly linear trend. The response of industrial production to an economic policy uncertainty shock is small and statistically insignificant on and near impact, followed by a period of statistically significant reductions only for the period 3-5 months. The peak negative impact is much smaller with a value of -0.18% at 5 months. The response turns out to be insignificant substantially earlier, compared to case 1. The same pattern holds for employment. The response of employment to an economic policy uncertainty shock is statistically significant at the interval 4-11 months, with the negative peak being -0.10% at 10 months. Again, the response turns out to insignificant quite earlier. In contrast, the pattern of the responses of industrial production and employment to a one standard deviation shock in S&P500 does not differ.

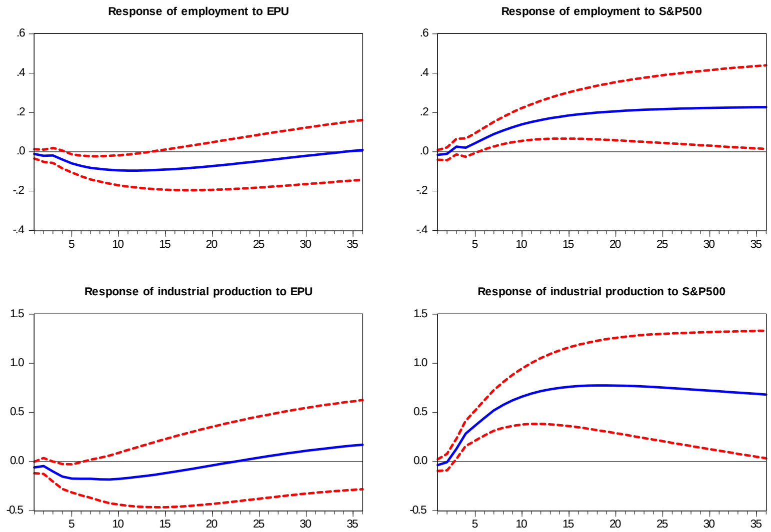

Fig. 3. Impulse response functions, case 2.

Thus, to summarize the patterns above, we find significant differences when reversing the order of economic policy uncertainty and S&P500, while the responses of industrial production and employment to an uncertainty shock appear to be insignificant on and near impact. These results differ from those of Baker et al. (2013).

We now reverse the real variable ordering by putting the macroeconomic variables first in the 5-VAR model. Our aim is to take into consideration some other recent studies in the relevant literature, such as Beetsma and Giuliodori (2013), Jurado et al. (2014), Popesku and Smets (2010) and Benati (2013), which assume - or consider as more reasonable - that shocks in economic uncertainty do not affect prices/interest rates and economic activity instantaneously (i.e. within the month). Rather, they assume the opposite direction. Thus, industrial production shocks might instantaneously affect e.g. the stock market or economic policy uncertainty, while shocks to the latter variables might affect industrial production or employment with a time lag. All these studies put the economic policy uncertainty index last.

Case 3: 5-VAR model, Cholesky ordering: industrial production, employment, effective federal funds rate, S&P500, EPU, 4 lags, monthly linear trend. As Figure 4 shows, the response of industrial production and employment is, as expected, zero on impact, while it is insignificant at all horizons. Thus, including real activity variables first and economic policy uncertainty last in the VAR model points to insignificant responses of the former variables to uncertainty shocks. On the other hand, responses of industrial production and employment to S&P500 shocks are similar to those of case 2.

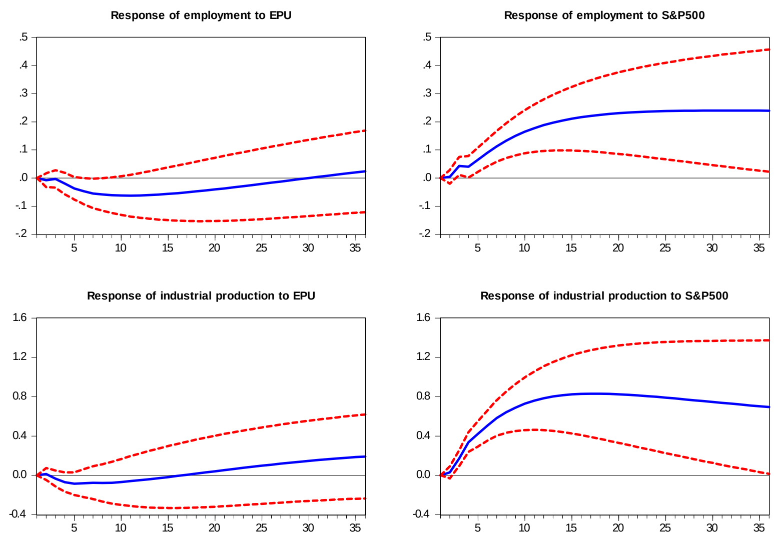

Fig. 4. Impulse response functions, case 3.

Case 4: 5-VAR model, Cholesky ordering: industrial production, employment, effective federal funds rate, EPU, S&P500, 4 lags, monthly linear trend. When putting macroeconomic activity variables first but reversing the order between S&P500 and EPU (i.e. including EPU before S&P500), then we get similar results with those of case 1.

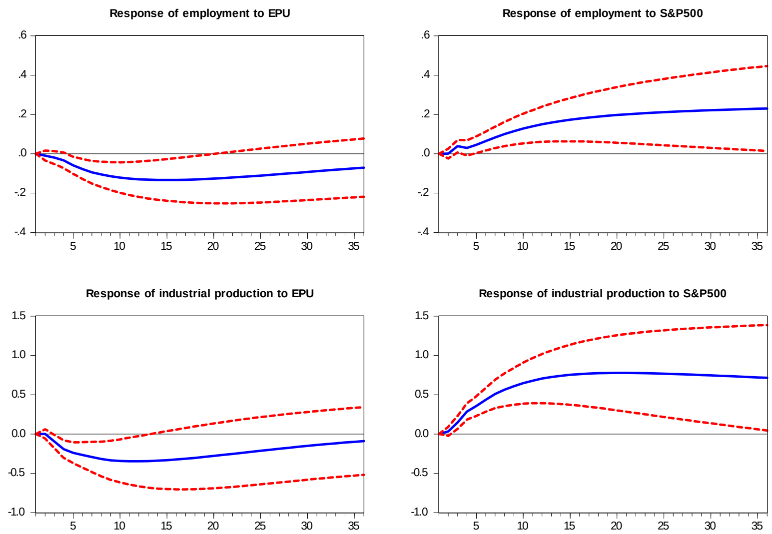

Fig. 5. Impulse response functions, case 4.

Figure 6 summarizes the response of industrial production to a one standard deviation shock in economic policy uncertainty based on different Cholesky orderings. The response becomes smaller or less deep when economic policy uncertainty is put at the end and/or after S&P500 in the VAR model.

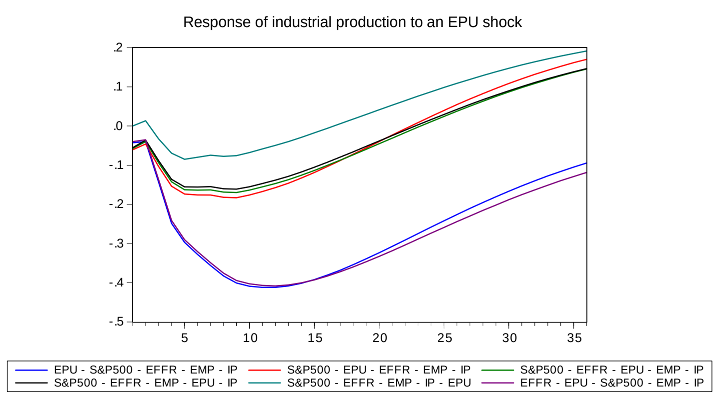

Fig. 6. Response of industrial production to a 1-standard deviation shock in EPU based on different Cholesky ordering.

Finally, we report impulse response results based on the structural shifts detrended VAR model.[27]

Case 5: 5-VAR model, Cholesky ordering: EPU, S&P500, effective federal funds rate, employment, industrial production, 4 lags, structural shifts detrending. When structural shifts are taken into account, i.e. when removed prior to estimating the VAR, then, in contrast to the results in case 1, the responses of industrial production and employment are insignificant at all horizons. The response of these variables to an innovation in S&P500 is similar as that in case 1, although now the response turns out to insignificant after several months ahead.

Case 6: 5-VAR model, Cholesky ordering: S&P500, EPU, effective federal funds rate, employment, industrial production, 4 lags, structural shifts detrending. As Figure 8 shows, the results are similar to those in case 5.

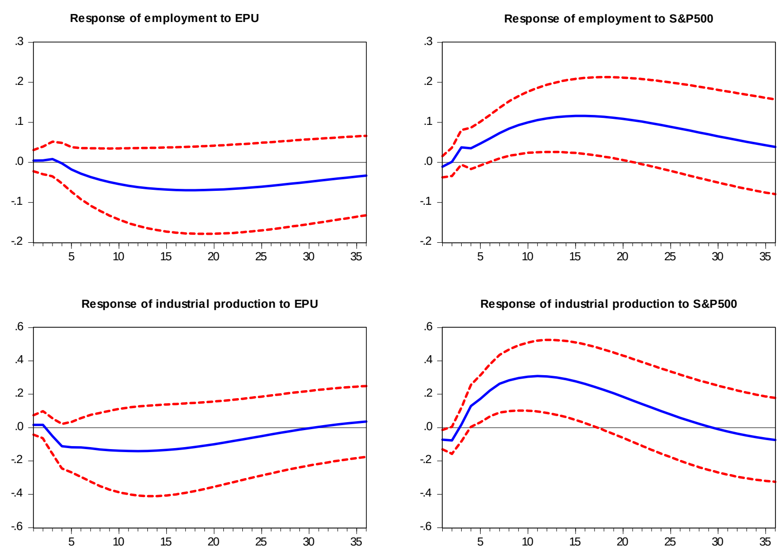

Fig. 7. Impulse response functions, case 5.

[27] We report results with 2 structural shifts in economic policy uncertainty. The results under 4 structural shifts do not differ.

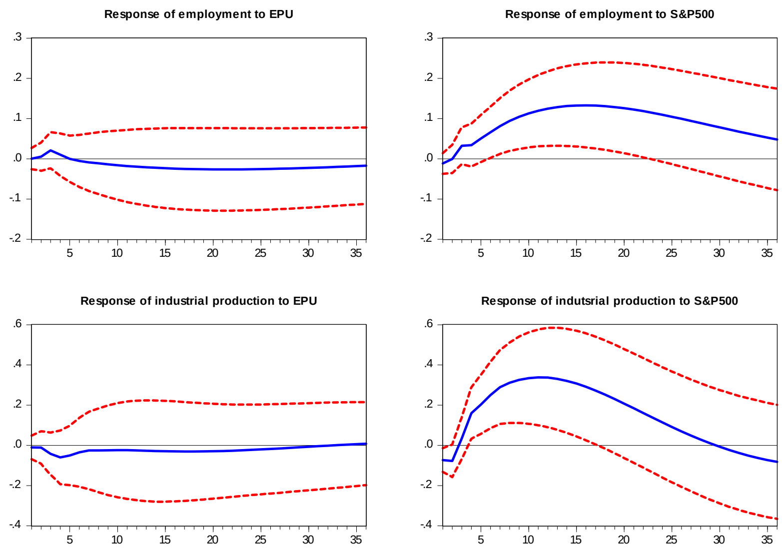

Fig. 8. Impulse response functions, case 6.

Combining the multi-horizon causality and the impulse response results, we find evidence close to the studies of Bachmann et al. (2013) and Cesa-Bianchi et al. (2014) who, although using different measures of uncertainty, different VAR models or different variable ordering, conclude weak responses of real activity to uncertainty shocks. In addition, our empirical analysis suggests that model specification, particularly with respect to the inclusion of a stock market performance variable, different Cholesky orderings and alternative treatment of trends results in different conclusions regarding the role of economic policy uncertainty in macroeconomic performance.

For example, the impulse response results suggest that when a shock in S&P500 is taken into account prior to an uncertainty shock, i.e. when the impact of the stock market is already controlled for when examining the effect of an uncertainty shock (cases 2,3), then the responses of industrial production and employment to an impulse in uncertainty are weakened. On the other hand, the effect of S&P500 appears to be almost the same regardless of the position of S&P500 in the VAR model. Multi-horizon causality results keep up with this result, since they show that it is the stock market variable rather than economic policy uncertainty, which contains predictive information for economic activity. In addition, the multi-horizon causality framework is capable of revealing that the predictive information from S&P500 to employment is transmitted through industrial production, implying indirect causality between the first two variables. Finally, orthogonal impulse responses keep up with the causality results from the detrended model, showing insignificant responses of industrial production and employment to uncertainty shocks once structural shifts are taken into account.

5 Robustness of the results

In this subsection we perform some robustness checks in order to verify that causality results remain unaffected by changes in the specification of the VAR model. Our robustness checks focus on (i) the replacement of the S&P500 index with the Dow Jones index (Dow Jones Industrial Average, DJIA) as a measure of the stock market performance and (ii) the inclusion of the VXO index as an additional variable in the VAR model, in order to control for financial uncertainty.[28]

The results are tabulated in Tables D2a, D2b, D2c, D3 in Appendix D and appear to be robust under both alternative VAR specifications. In case (i), under the standard linear trend (Table D2a), the (logarithm of) Dow Jones index still helps to anticipate industrial production directly, at all horizons, and employment indirectly through industrial production, at horizons $h = 6 - 7$. Economic policy uncertainty appears to contain limited - based on significant horizons - predictive information for employment, while we now observe some causal effects for industrial production albeit only in the short-run, at $h = 1, 2$, and with a p-value larger than 0.05. Industrial production has still been found to contain predictive information for the other system variables. When infrequent trend breaks are taken into account, the results with DJIA keep up with the previous S&P500 related 5-VAR findings: economic policy uncertainty does not anticipate industrial production and employment, while the Dow Jones index does cause both these variables.

In case (ii), when the VXO index (a leading index of stock market uncertainty based on asset prices) is included as an additional variable in the VAR model[29] our results also do not differ. Table D3 shows that EPU does not help to

[28] We include the VXO index (volatility index prices using the old methodology) instead of the VIX index (volatility index prices using the new methodology), because the VXO data are available from 1986 onwards (monthly frequency) whereas VIX data start in 1990. Both indices are provided by the Chicago Board of Options and Exchange (CBOE).

[29] Notice that Baker et al. (2013) report correlation between VIX - EPU on the order of

anticipate industrial production or employment (the null hypothesis is rejected at $h = 1 - 3$ for employment, albeit at the 10% significance level), while the second measure of uncertainty, VXO, does not also contain predictive information for real economic activity (the weak p-value of 0.0975 at $h = 1$ does not allow us to infer any strong causal relation from VXO to industrial production). On the other hand, the stock market level still has (a) direct predictive content for industrial production and (b) indirect predictive content for employment through its effect on industrial production.

6 Conclusions

In this paper we examine the role of economic policy uncertainty in aggregate real economic activity in the US before and after the removal of infrequent trend breaks and before and after the introduction of the stock market level as an additional controlling variable in reduced form VAR models.

The multi-horizon concept of Granger causality that we employ takes into account all possible combinations via which predictive information might be transmitted, since, under the employment of high-dimensional VARs, it can reveal additional information on multiple causal channels and the presence of causal chains among the system variables. Multiple horizon or indirect causality might occur between two variables of direct interest at higher forecast horizons, revealing nuanced details on multiple-horizon causation which would be collapsed out when employing standard Granger causality test procedures (or when employing low-dimensional VARs).

Structural shifts represent infrequent changes in economic fundamentals and may affect the trend function in a permanent way so that they can be modeled as part of the deterministic trend component. Non-modeling of "rare" or "infrequent" events that yet affect the long-run part of the time series introduces additional nonstationarity in the VAR model, which might lead to inconsistent VAR estimates and it can drive Granger causality tests to over-reject the null hypothesis of non-causality. In addition, in terms of methodological consistency, structural breaks should be also included in the multivariate setting, once they are found to be present in univariate series.

Our empirical investigation of the economic policy uncertainty - real eco-

0.578. Beyond being positive, this estimation also points to substantial independent variation in both indices. Indeed, the respective errors in our VAR estimation are contemporaneously correlated with correlation around 0.410.

nomic activity causality shows that the predictive ability of economic policy uncertainty for real economic activity significantly depends on the presence (or absence) of infrequent structural shifts in the time series employed and the absence of relevant variables (stock market level) from the information set. Introducing stock prices renders policy uncertainty noninformative for the industrial production series irrespective of trend removal. There is some evidence that policy uncertainty affects employment prior to the removal of a small number of secular changes from the series mean levels and growth rates. After removing these rare events, policy uncertainty does not Granger cause activity at any forecast horizon. In contrast, stock prices, irrespective of the removal of two changes in the secular growth rates of the activity variables, are found to contain strong predictive information for economic activity, directly to industrial production and indirectly to employment (through industrial production).

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Table 1. Summary results for deterministic component breaks and unit root tests

Series	Break location				Noise component
(log) Industrial production	1993m8 (104)	1999m12 (180)			I(1) with or without trend breaks
	Sample segment				
	1985m1 - 1993m8	1993m9 - 1999m12	2000m1 - 2013m8		
Annual growth rate %	2.02	5.34	0.40		
Series	Break location				Noise component
(log) Employment	1989m04 (52)	2006m10 (264)			I(1) with or without trend breaks
	Sample segment				
	1985m1 - 1989m4	1989m5 - 2006m10	2006m11 - 2013m8		
Annual growth rate %	2.36	1.30	-0.40		
Series	Break location				Noise component
EPU (2 breaks)	1993m9 (105)	2008m8 (284)			I(0) with or without mean breaks
Mean level change %	-20.77	76.97			
Series	Break location				Noise component
EPU (4 breaks)	1993m9 (105)	2000m10 (190)	2003m5 (221)	2008m8 (284)	I(0) with or without mean breaks
Mean level change %	-27.11	43.08	-27.65	85.83	

Notes. Appendix C describes all testing procedures employed. Annual growth rates are based on OLS estimation of the first differenced model . % mean level changes are based on OLS estimation of the economic policy uncertainty index on mean shift dummies. Break location reports estimated break dates (last observation in each subsample) while in parentheses, we report sample observation number.

Table 2. Toda-Yamamoto causality results - standard linear trend included

2-VAR	p-value	4-VAR	p-value	5-VAR	p-value		p-value
EPU $\nrightarrow$ IP	0.0005	EPU $\nrightarrow$ EFFR	0.0000	EPU $\nrightarrow$ S&P500	0.0740	EMP $\nrightarrow$ EPU	0.0441
IP $\nrightarrow$ EPU	0.2692	EPU $\nrightarrow$ EMP	0.4244	EPU $\nrightarrow$ EFFR	0.0008	EMP $\nrightarrow$ S&P500	0.6573
		EPU $\nrightarrow$ IP	0.0011	EPU $\nrightarrow$ EMP	0.0526	EMP $\nrightarrow$ EFFR	0.2433
3-VAR	p-value	EFFR $\nrightarrow$ EPU	0.7699	EPU $\nrightarrow$ IP	0.6288	EMP $\nrightarrow$ IP	0.2520
EPU $\nrightarrow$ EMP	0.0391	EFFR $\nrightarrow$ EMP	0.4731	S&P500$\nrightarrow$ EPU	0.0020	IP $\nrightarrow$ EPU	0.2105
EPU $\nrightarrow$ IP	0.0002	EFFR $\nrightarrow$ IP	0.7543	S&P500$\nrightarrow$ EFFR	0.4283	IP $\nrightarrow$ S&P500	0.0010
EMP $\nrightarrow$ EPU	0.0405	EMP $\nrightarrow$ EPU	0.0091	S&P500$\nrightarrow$ EMP	0.0407	IP $\nrightarrow$ EFFR	0.0097
EMP $\nrightarrow$ IP	0.2825	EMP $\nrightarrow$ EFFR	0.6302	S&P500$\nrightarrow$ IP	0.0000	IP $\nrightarrow$ EMP	0.0065
IP $\nrightarrow$ EPU	0.2258	EMP $\nrightarrow$ IP	0.0437	EFFR $\nrightarrow$ EPU	0.9597		
IP $\nrightarrow$ EMP	0.0008	IP $\nrightarrow$ EPU	0.0696	EFFR $\nrightarrow$ S&P500	0.2772		
		IP $\nrightarrow$ EFFR	0.0085	EFFR $\nrightarrow$ EMP	0.8858		
		IP $\nrightarrow$ EMP	0.0029	EFFR $\nrightarrow$ IP	0.7618		

Notes. EPU, S&500, EFFR, EMP, IP correspond to economic policy uncertainty, Standard&Poor 500, effective federal funds rate, employment and industrial production, respectively. The null hypothesis is that the left side variable in each column does not cause ($\nrightarrow$) the right side variable.

Table 4. Toda-Yamamoto causality results - structural shifts in linear trend included: 2 level shifts in EPU

2-VAR	p-value	4-VAR	p-value	5-VAR	p-value		p-value
EPU $\nrightarrow$ IP	0.0034	EPU $\nrightarrow$ EFFR	0.0000	EPU $\nrightarrow$ S&P500	0.0521	EMP $\nrightarrow$ EPU	0.2198
IP $\nrightarrow$ EPU	0.6501	EPU $\nrightarrow$ EMP	0.9096	EPU $\nrightarrow$ EFFR	0.0005	EMP $\nrightarrow$ S&P500	0.5124
		EPU $\nrightarrow$ IP	0.0268	EPU $\nrightarrow$ EMP	0.4344	EMP $\nrightarrow$ EFFR	0.2159
3-VAR	p-value	EFFR $\nrightarrow$ EPU	0.7499	EPU $\nrightarrow$ IP	0.8807	EMP $\nrightarrow$ IP	0.1918
EPU $\nrightarrow$ EMP	0.5157	EFFR $\nrightarrow$ EMP	0.6831	S&P500$\nrightarrow$ EPU	0.0227	IP $\nrightarrow$ EPU	0.2601
EPU $\nrightarrow$ IP	0.0051	EFFR $\nrightarrow$ IP	0.2730	S&P500$\nrightarrow$ EFFR	0.2488	IP $\nrightarrow$ S&P500	0.0067
EMP $\nrightarrow$ EPU	0.1234	EMP $\nrightarrow$ EPU	0.0520	S&P500$\nrightarrow$ EMP	0.0256	IP $\nrightarrow$ EFFR	0.0022
EMP $\nrightarrow$ IP	0.0449	EMP $\nrightarrow$ EFFR	0.8493	S&P500$\nrightarrow$ IP	0.0001	IP $\nrightarrow$ EMP	0.0108
IP $\nrightarrow$ EPU	0.4214	EMP $\nrightarrow$ IP	0.0034	EFFR $\nrightarrow$ EPU	0.8997		
IP $\nrightarrow$ EMP	0.0016	IP $\nrightarrow$ EPU	0.7441	EFFR $\nrightarrow$ S&P500	0.0625		
		IP $\nrightarrow$ EFFR	0.0005	EFFR $\nrightarrow$ EMP	0.9121		
		IP $\nrightarrow$ EMP	0.0012	EFFR $\nrightarrow$ IP	0.7306		

Notes. EPU, S&500, EFFR, EMP, IP correspond to economic policy uncertainty, Standard&Poor 500, effective federal funds rate, employment and industrial production, respectively. The null hypothesis is that the left side variable in each column does not cause ($\nrightarrow$) the right side variable.

Table 6. Toda-Yamamoto causality results - structural shifts in linear trend included: 4 level shifts in EPU

2-VAR	p-value	4-VAR	p-value	5-VAR	p-value		p-value
EPU $\nrightarrow$ IP	0.0102	EPU $\nrightarrow$ EFFR	0.0000	EPU $\nrightarrow$ S&P500	0.0015	EMP $\nrightarrow$ EPU	0.1742
IP $\nrightarrow$ EPU	0.7279	EPU $\nrightarrow$ EMP	0.8182	EPU $\nrightarrow$ EFFR	0.0041	EMP $\nrightarrow$ S&P500	0.5250
		EPU $\nrightarrow$ IP	0.0189	EPU $\nrightarrow$ EMP	0.5404	EMP $\nrightarrow$ EFFR	0.2320
3-VAR	p-value	EFFR $\nrightarrow$ EPU	0.8360	EPU $\nrightarrow$ IP	0.7179	EMP $\nrightarrow$ IP	0.1718
EPU $\nrightarrow$ EMP	0.7923	EFFR $\nrightarrow$ EMP	0.4708	S&P500$\nrightarrow$ EPU	0.2787	IP $\nrightarrow$ EPU	0.3931
EPU $\nrightarrow$ IP	0.0094	EFFR $\nrightarrow$ IP	0.2161	S&P500$\nrightarrow$ EFFR	0.2155	IP $\nrightarrow$ S&P500	0.0041
EMP $\nrightarrow$ EPU	0.1178	EMP $\nrightarrow$ EPU	0.0572	S&P500$\nrightarrow$ EMP	0.0389	IP $\nrightarrow$ EFFR	0.0037
EMP $\nrightarrow$ IP	0.0407	EMP $\nrightarrow$ EFFR	0.8414	S&P500$\nrightarrow$ IP	0.0000	IP $\nrightarrow$ EMP	0.0093
IP $\nrightarrow$ EPU	0.5228	EMP $\nrightarrow$ IP	0.0027	EFFR $\nrightarrow$ EPU	0.9274		
IP $\nrightarrow$ EMP	0.0007	IP $\nrightarrow$ EPU	0.7965	EFFR $\nrightarrow$ S&P500	0.0263		
		IP $\nrightarrow$ EFFR	0.0004	EFFR $\nrightarrow$ EMP	0.8168		
		IP $\nrightarrow$ EMP	0.0009	EFFR $\nrightarrow$ IP	0.6962		

Notes. EPU, S&500, EFFR, EMP, IP correspond to economic policy uncertainty, Standard&Poor 500, effective federal funds rate, employment and industrial production, respectively. The null hypothesis is that the left side variable in each column does not cause ($\nrightarrow$) the right side variable.

Table 3a. 3 - 4 VAR DPR causality results: standard linear trend included

	Predicted				**Predicted**			
3 VAR	EPU	EMP	IP	4 VAR	EPU	EFFR	EMP	IP
Predictor				**Predictor**				
EPU		$1-5$	$1-5$	EPU		$1-5$	$3-5$	$1-5$
EMP	$1^{(**)}$			EFFR				
IP		$1-5$		EMP	1			$1-4$
				IP		1	$1-5$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 5$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table 3b. 5 -VAR DPR causality results - standard linear trend included

	Predicted				
	EPU	S&P500	EFFR	EMP	IP
Predictor					
EPU			$1-13$	$1^{(**)}, 2-4, 6^{(**)}$	
S&P500	$1-7$			$10-13^{(**)}$	$1-13$
EFFR					
EMP	$1, 7^{(**)}, 8$				
IP		$1, 2^{(**)}$	$1, 6^{(**)}, 7, 8-9^{(**)}, 13^{(**)}$	$1-5, 6-7^{(**)}$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 13$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table 5a. 3 - 4 VAR DPR causality results: structural shifts in linear trend included: 2 level shifts in EPU

	Predicted				**Predicted**			
3 VAR	EPU	EMP	IP	4 VAR	EPU	EFFR	EMP	IP
Predictor				**Predictor**				
EPU			$1-4$	EPU		$1-5$		$1-3, 4^{(**)}$
EMP			$1, 2-3^{(**)}, 4$	EFFR				
IP		$1-5$		EMP				$1-5$
				IP		1	$1-5$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 5$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the10% (cases with **) significance level.

Table 5b. 5 - VAR DPR causality results - structural shifts in linear trend included: 2 level shifts in EPU

	Predicted				
	EPU	S&P500	EFFR	EMP	IP
Predictor					
EPU		$1-7, 8^{(**)}$	$1-8, 9-13^{(**)}$		
S&P500	$1-2^{(**)}, 3$		$3^{(**)}, 4, 5-6^{(**)}$	$1^{(**)}, 2, 4-13$	$1-6, 7^{(**)}$
EFFR	$8^{(**)}$	$1-9, 10^{(**)}$			
EMP	$8-9, 11^{(**)}, 12$				
IP	$6^{(**)}, 7, 8^{(**)}, 13$	$1-2, 3-4^{(**)}$, $5-11, 12-13^{(**)}$	$1^{(**)}, 6^{(**)}, 7$, $8-9^{(**)}, 12-13^{(**)}$	$1-5, 6^{(**)}$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 13$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table 7a. 3 - 4 VAR DPR causality results: structural shifts in linear trend included: 4 level shifts in EPU

	Predicted				**Predicted**			
3 VAR	EPU	EMP	IP	4 VAR	EPU	EFFR	EMP	IP
Predictor				**Predictor**				
EPU			$1-3, 4^{(**)}$	EPU		$1-5$		$1-3, 4^{(**)}$
EMP			$1, 2-3^{(**)}, 4$	EFFR			$5^{(**)}$	
IP		$1-5$		EMP				$1-4, 5^{(**)}$
				IP		$1, 2^{(**)}$	$1-5$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 5$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table 7b. 5 - VAR DPR causality results - structural shifts in linear trend included: 4 level shifts in EPU

	Predicted				
	EPU	S&P500	EFFR	EMP	IP
Predictor					
EPU		$1-8$	$1-3, 4-5^{(**)}$		
S&P500			$3^{(**)}, 4$	$2^{(**)}, 4-11$, $12-13^{(**)}$	$1-8, 9^{(**)}$, $10, 11-13^{(**)}$
EFFR	$6-9$	$1-11, 12-13^{(**)}$			
EMP	$9^{(**)}, 11^{(**)}, 12$				$2^{(**)}$
IP	$7, 13$	$1-2, 3^{(**)}$, $4-11, 12^{(**)}$	$6^{(**)}, 7$, $8-9^{(**)}, 13^{(**)}$	$1-5$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 13$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Appendix to "Economic policy uncertainty and economic activity: a focus on infrequent structural shifts" by Paraskevi Salamaliki

A Data sources

Economic policy uncertainty index. Monthly data, 1985M01-2013M08. Source: Baker et al. (2013), `www.policyuncertainty.com`

Industrial Production. Monthly data, 1985M01-2013M08. Downloaded from FRED Economic Database (Series ID: INDPRO), Source: Board of Governors of the Federal Reserve System, `http://research.stlouisfed.org/fred2/series/INDPRO/`

Employment (Civilian). Monthly data, 1985M01-2013M08. Downloaded from FRED Economic Database (Series ID: CE16OV), Source: US Department of Labor: Bureau of Labor Statistics, `http://research.stlouisfed.org/fred2/series/CE16OV`

Effective Federal Funds Rate. Monthly data, 1985M01-2013M08. Downloaded from FRED Economic Database (Series ID: FEDFUNDS), Source: Board of Governors of the Federal Reserve System, `http://research.stlouisfed.org/fred2/series/FEDFUNDS/`

S&P500 stock price index. Monthly data (average), 1985M01-2013M08. Downloaded from FRED Economic Database (Series ID: SP500), Source: SP Dow Jones Indices LLC, `http://research.stlouisfed.org/fred2/series/SP500/downloaddata`

B Testing for short-run and long-run causality: Dufour, Pelletier and Renault (2006)

Dufour and Renault (1998) suggest a general definition of non-causality at various horizons ($h \geq 1$) and up to a certain horizon, h, with respect to a "reference information set". Their definition provides a natural extension to the standard Granger (1969) causality definition and is based on linear predictability on higher forecast horizons, while for the horizon one ($h = 1$) it includes the special case of the Granger (1969) concept of causality. More precisely, the Dufour and Renault (1998) emphasizes on the role of the forecast horizon, h, while the concept of extended (or multi-horizon) causality embodies both the standard notion of Granger causality ($h = 1$) and indirect causality ($h > 1$). This definition also permits the distinction between short-run causality (small forecast horizon) and long-run causality (long forecast horizon).

Based on Dufour and Renault (1998), Dufour et al. (2006) propose simple tests for non-causality restrictions at various horizons for finite-order vector autoregressive (VAR) models, which can be implemented through linear regression methods.

The point of origin is OLS estimation of the following autoregression of order p at horizon h, named (p, h)-autoregression by DPR,

$$W_{t+h} = \mu + \sum_{k=1}^{p} \pi_k^{(h)} W_{t+1-k} + u_{t+h}^{(h)}$$

where W_{t+h} is the projection of the (standard) VAR framework at any horizon h, given the available information at time t. Dufour and Renault (1998) provide the appropriate analytic formulas of the coefficients $\pi_k^{(h)}$ (see equations 3.7, 3.8, 3.16, 3.17 in particular), as well as the (p, h)-autoregression expressed in matrix form. In the case of nonstationarity for some or all variables in VAR model, the (p, h)-autoregression is extended in the Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) fashion by adding d extra lags to the VAR models, with d denoting the largest order of integration for the W_t vector process.

Dufour et al. (2006) device a simple Wald test of linear zero restrictions to test for $h-$step ahead non-causality based on restricting the appropriate block of the $\pi_k^{(h)}$coefficients for all lags ($k \geq 1$). Under the null hypothesis of non-causality between the two variables of interest at horizon h, the χ_p^2 asymptotic distribution of the Wald statistic may not be very reliable in finite samples, and in view of the fact that the test statistics are asymptotically pivotal under the null hypothesis, it is recommended to apply the parametric bootstrap method considered by Dufour et al. (2006). In our study, the number of replications is set at $10,000$. The bootstrap procedure is presented in detail in Dufour et al. (2006, p.351).

C Testing for structural trend breaks and unit roots

Industrial production and employment

We apply a range of new econometric techniques to the log industrial production and log employment series that are robust to the presence of an $I(1)$ or $I(0)$ noise component and enable (a) detection of breaks in the linear trend function; emphasis placed on slope shifts, (b) estimation of the number of breaks, (c) estimation of the break locations. Further, we apply a new set of powerful unit root tests that allow for structural breaks under both the null and alternative hypotheses.

The first stage of our testing procedure involves the use of Perron and Yabu (2009, henceforth PY) and Harvey et al. (2009, henceforth HLTa) tests for a one-time break in the trend function. The PY test is based on a quasi-feasible generalized least squares procedure with improved finite sample properties due to the use of a bias-corrected version of the underlying autoregressive parameter (α in equation (2)). PY show that their procedure has a power function close to that attainable if one knew the true value of α under many circumstances. The HLTa test uses a data-dependent weighted average of the supremum of regression t-statistics for a broken trend under the case of either $I(0)$ or $I(1)$ noise. HLTa employ a weight function based on auxiliary KPSS type statistics and choose the value of certain constants arising in their procedure so that the test exhibits both acceptable size and decent power across the range of simulation experiments they considered. An advantage of the PY test is found in that it does not employ any random scaling so that it is more prone to have higher power and less size distortions. Indeed, Chun and Perron (2013) analyze the finite sample size and power properties of these tests under a variety of data-generating processes and show that the PY test has greater power overall whereas, with respect to size, the HLTa test exhibits larger size distortions unless a moving-average component is present.

Then, we apply the Kejriwal and Perron (2010, henceforth KP) sequential procedure, that extends the work of PY in the direction of multiple breaks in slope or multiple simultaneous breaks in slope and level. Again, the KP procedure allows one to consistently estimate the true number of breaks irrespective of whether the errors are $I(0)$ or $I(1)$. The procedure sequentially tests the null hypothesis of l breaks, against the alternative hypothesis of $(l+1)$ breaks. Monte Carlo experiments by KP showed that the procedure performs adequately in finite samples. In theory, the maximum number of breaks m in (1), is treated as unknown. When the sequential procedure fails to reject the null hypothesis of no additional breaks, then the maximum number of breaks has been determined. However, KP simulations showed that there is a non-negligible probability of overestimation of the number of breaks that increases as α increases in (8) and as we increase the number of breaks assumed under the null hypothesis. This is particular true for the model that allows simultaneous level and slope changes. Hence, KP point out that caution should be exercised with respect to the maximum number of breaks permissible. In addition, a sufficient number of observations must be allowed within segments since successively smaller data subsamples (as more breaks are allowed) lead to further power and/or size distortions. Finally, allowing for a large number of breaks is not an appropriate strategy if one wants to determine if a unit root in the noise component is present or if one wants to evaluate the impact of large permanent but infrequent shocks. On one hand, the unit root process can be viewed as a limiting case of a stationary process with multiple breaks, one that has a break (permanent shock) every period. On the other, a stationary process with multiple trend breaks could provide successful in-sample curve fitting mimicking unit root behavior but permitting for frequent permanent shocks with smaller magnitudes. Hence, given our sample size of 344 monthly observations, we set a maximum of 2 breaks in the deterministic component that allows for a minimum subsample length of less than 9.5 years or 114 observations.

In the second stage, we apply powerful unit root tests that allow for (multiple) structural breaks under both the null and alternative hypotheses proposed by Carrion-i-Silvestre et al. (2009, henceforth CKP) and Harvey et al. (2013, MDF1 and MDF2 tests). The CKP tests are based on a quasi-generalized least squares detrending method and bear the heading "GLS" in Table C1. The tests have local asymptotic power functions close to the local asymptotic Gaussian power envelope, hence they deliver near asymptotically efficient unit root inference, provided the break magnitudes are fixed. However, in finite samples, the power functions might exhibit "valleys" for specific break magnitude widths that often appear in economic time series. For this reason, we also employ the Harvey et al. (2013, MDF1 and MDF2) tests, which are applied only to the broken slope trend model, and have superior power properties for magnitudes of trend breaks typically observed in practice. These tests are based on the infimum of a sequence of local GLS detrended augmented Dickey-Fuller type statistics.

Finally, when at least one break in trend has been identified and $I(1)$ behavior under the trend break is not ruled out, we proceed with consistent estimation of the break fraction locations as outlined in CKP, Section 5.1. Under the assumptions of trend breaks and unit root, the CKP estimator of the break fractions converges at a superconsistent rate. The CKP estimator is based on global minimization of the residual sum of squares of the GLS detrended model (7) and (8) where a regular grid search over one or two breaks has been employed. The necessary noncentrality parameter for the GLS detrending is given by CKP, table1, p.1761.

The results of the procedure described above are presented in Table C1 and clearly point to a strong rejection of the null hypothesis that the trend function is stable in favor of a trend function with two shifts for both the log industrial production and log employment series. The $F(1|0)$ statistic for both series and the HLTa for the log-employment strongly reject at the 1% significance level the null of no trend break. The non-rejection by the HLTa test can be ascribed to its lower power compared to that of PY (see Chun and Perron, 2013)[1]. Upon rejection of the one-time break tests, we use the $F(2|1)$ test to determine if there is more than one break. Again, in both series the null is strongly rejected at the 1% significance level. Next we examine the unit root test results. For the log-industrial production, under two trend breaks present, we find that the PT_GLS, MPT_GLS tests and the MDF2 test do not reject the null hypothesis of a unit root, while the three remaining GLS tests, MZa_GLS, MZt_GLS, MSB_GLS reject the unit root null but only near the 10% asymptotic critical value. The unit root tests for the log-employment series unanimously fail to reject the null of a unit root when permitting for two trend breaks. Hence, we conclude in favor of unit root behavior in both series in addition to the presence of two large permanent shocks that affected the average growth paths of both

[1] We further suspect that the non-monotonic slope change of the trend component (the slope significantly increases in the first break and significantly decreases in the second) might contribute to the non-rejection of a single break by the test.

Table C1. Tests for trend breaks allowing I(0) or I(1) errors and unit root tests conditional on the absence/presence of trend breaks

	Series			Unit root tests - 1 or 2 Breaks						
Test	logip	break location		PT_{GLS}	MPT_{GLS}	MZ^a_{GLS}	MZ^t_{GLS}	MSB_{GLS}	MDF_1	MDF_2
$F(1\|0)$	17.146a	2000m09 (189)		8.711	8.408	-18.258	-3.016	0.165	-3.177	
$F(2\|1)$	15.547a	1993m08 (104)	1999m12 (180)	9.103	9.071	-26.196c	-3.595c	0.137c		-3.769
$HLTa$	2.112									
	logemp	break location		PT_{GLS}	MPT_{GLS}	MZ^a_{GLS}	MZ^t_{GLS}	MSB_{GLS}	MDF_1	MDF_2
$F(1\|0)$	18.719a	2006m10 (264)		18.864	17.688	-7.129	-1.827	0.256	-2.198	
$F(2\|1)$	15.332a	1989m04 (52)	2006m10 (264)	18.850	18.723	-11.247	-2.286	0.203		-2.380
$HLTa$	3.232a									

Notes. logip and logemp are the log industrial production and log employment series respectively. a,b and c denote significance at the 1%, 5% and 10% significance level, also marked by bold types. In all tests, a trimming of 15% both at the beginning and the end of the sample has been considered. F(1|0) and HLTa are the Perron and Yabu (2009) and Harvey et al. (2009) tests for a single break in the trend function. Critical values are given in Perron and Yabu (2009), Table 2c, p.374 and in Harvey et al. (2009) Table 1, p.1007 respectively. F(2|1) is the Kejriwal and Perron (2010) sequential test of one (1) versus two (2) trend breaks respectively. Critical values are given in Kejriwal and Perron (2010), Table 1, p.309. Break location reports estimated break dates (last observation in each subsample) while in parentheses, we report sample observation number. For example, September 2000 (2000m9) corresponds to the 189th sample observation. Under the "GLS" column headings, we report the GLS-detrended unit root tests of Carrion-i-Silvestre et al. (2009). Critical values can be found in Tables 2A, 2B, 2C, 2D in Carrion-i-Silvestre et al. (2009). Under column headings "MDF_1" and "MDF_2" we report the minimum Dickey-Fuller statistics of Harvey et al. (2013). Critical values can be found in Harvey et al. (2013), Table 1, p.268.

series. Finally, Table C1 also presents estimates of the break dates obtained using the CKP method, namely (end-sample dates): 1993m08 (observation number 104), 1999m12 (observation number 180) for log-industrial production and 1989m04 (observation number 52), 2006m10 (observation number 264) for the log-employment series. More discussion on these dates can be found in text.

Economic Policy Uncertainty index

Both visual inspection and theoretical considerations compel us to treat economic policy uncertainty as an inherently non-trending series that might exhibit mean level shifts. It would be far fetched to assume a long- run deterministic trend or an infrequently segmented trend in the series with rising or decreasing uncertainty levels that cover the entire sample span (1985 - 2013). A similar argument would apply to the hypothesis of a unit root in the uncertainty series. Such a hypothesis would imply a series of permanent shocks affecting the series path, and an increasing underlying variance. Figure C1 shows the sample autocorrelation function of EPU for lags 1 to 36. The dotted line in the autocorrelation plot is the approximate 5% two standard error bound computed as $2/\sqrt{T}$. The figure provides evidence that although correlated, the series might be stationary.

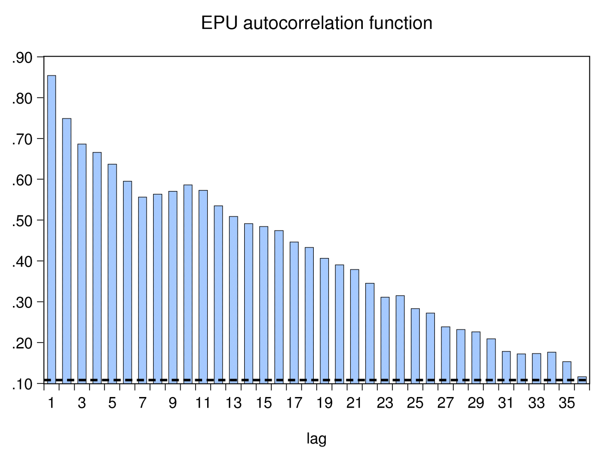

Fig C1. EPU autocorrelation function

Table C2 shows the results for a number of unit root tests computed for both the EPU series and the log(EPU) series in levels and in first differences. Almost all tests indicate that the hypothesis of a unit root can be rejected for each of the level or first differenced series, supporting the assumption of stationarity. The non-rejection of the unit root hypothesis by the ADF test is not surprising as it is known to have low power when structural breaks are ignored. This is particularly true when more than one break might be present. The same remark applies to the weak rejection of the null hypothesis of stationarity observed for the KPSS statistic on the series. One or more breaks can induce spurious persistence and although the number of augmentation lags have been selected using the MAIC criterion following the suggestion in Perron and Qu (2007), the number of lags is still large enough (9 lags) to affect variance computations. Hence, under the assumption of stationarity for the economic policy uncertainty series, we proceed to test for abrupt structural changes in the mean of the EPU series. We use the sequential statistical techniques of Bai (1997), Bai and Perron (1998, 2003) to test for the number of breaks and to date the break locations without prior knowledge of when these breaks occur. In addition, we employ information criteria techniques to estimate the number of breaks such as the Bayesian Information Criterion (BIC) suggested by Yai (1988), the modified Schwarz criterion (LWZ) suggested by Liu et al. (1997) and the Hannan and Quinn (1979, HQ) criterion. The information criteria approach is made more reliable by further employing the modified penalty functions proposed by Hall et al. (2013), referred to as BICC and HQC respectively. The authors provide simulation evidence of substantial improvement in the overall performance of both the BIC and HQ criteria even in the presence of serial correlation and when sequential testing might not perform well. The results of all testing procedures are summarized in Table C3. The sequential type 1 and sequential type 2 methods differ on how they select the additional breakpoint if present. In type 1, each segment is sequentially tested for a break while in type 2 the most important break in terms of residual sum of squares is included sequentially, if the null is rejected. In both procedures a repartition procedure described in Bai (1997) has been applied. The sequential type 3 procedure is based upon the sequential procedure explained in Bai and Perron (1998, 2003) and it employs global minimization of the sum-of-squared residuals at each testing step of l versus $l+1$ breaks. We allowed up to a maximum number of $m = 8$ or $m = 9$ breaks using a trimming of $\varepsilon = 0.10$ or $\varepsilon = 0.05$ respectively, hence each segment has at least $h = 34$ or $h = 17$ observations (months). Notice that, if we set h

Table C2. Unit root test statistics for EPU and log(EPU)

				Levels					
Series	ADF	PP	$KPSS$	$DF-GLS$	MZa	MZt	MSB	MPT	$ERSP.O$
EPU	-1.8685	-4.7767a	0.5203b	-1.8776c	-7.0146c	-1.8728c	0.2670c	3.4927c	3.4679c
log(EPU)	-1.8594	-4.5665a	0.4189a	-1.8153c	-6.5917c	-1.8154c	0.2754	3.7168c	3.6577c
				First differences					
EPU	-21.188a	-27.813a	0.0502	-10.715a	-129.232a	-8.016a	0.062a	0.226a	0.431a
log(EPU)	-21.880a	-28.920a	0.0601	-9.695a	-116.289a	-7.600a	0.065a	0.255a	0.533a

Notes. a,b, and c denote significance at the 1%, 5% and 10% significance levels also marked by bold types. The deterministic component is made up of a constant. Augmentation lags have been selected using the MAIC criterion calculated following the suggestion in Perron and Qu (2007). The series under test are: the economic policy uncertainty index (EPU) and its natural logarithmn log(EPU).

Table C3. EPU break test results

method	Specification $M = 9, \varepsilon = 0.05, h = 17$ ranked break locations								
Sequential type 1			105					284	
Sequential type 2			105					284	
Sequential type 3			105					284	
BIC	40	64	105	190	220	239	267	284	
BICC			105	190	221			284	
HQ	40	64	105	190	220	239	267	284	306
HQC			105	190	221			284	
LWZ			105	190	221			284	
method	Specification $M = 8, \varepsilon = 0.10, h = 34$ ranked break locations								
Sequential type 1			105					284	
Sequential type 2			105					284	
Sequential type 3			105					284	
BIC			105	190	225			284	
BICC			105	190	225			284	
HQ		64	105	190	225			284	
HQC			105	190	225			284	
LWZ			105	190	225			284	

Notes. We use a maximum of M breaks, $(100 * \varepsilon)\%$ trimming that determines the minimum subsample segment length (h observations) permitted and, in all tests, we employ a nominal size of 0.05. Estimated breakpoint locations correspond to the last observation within a segment. The observation correspodence to actual sample dates is as follows (i) 105: 1993m9, (ii) 190: 2000m10, (iii) 221: 2003m5 , (iv) 284: 2008m8. These are the dates employed in our analysis for the two and four breaks cases.

too low, we might pick up spurious effects. On the other hand, setting h too high, limits the sample and increases the probability of missing important break points. In the sequential procedures, we allow for serial correlation and heterogeneous error distributions across segments (HAC variances are computed using the Andrews (1991) automatic bandwidth with AR(1) approximation method and the Bartlett kernel).

According to Table C3, the sequential procedures are rather conservative and find two breaks located at 1993m9 (end of subsample date, observation 105) and 2008m8 (end of subsample date, observation 284), while the corrected information criteria of Hall et al. (2013) find two additional breaks located at 2000m10 (end of subsample date, observation 190) and 2003m5 (end of subsample date, observation 221). Notice that the corrected information criteria approach may be more powerful than the sequential approach, especially for certain configurations of non-monotonic changes in the mean level.

The aforementioned sample locations designate the dates employed in our analysis for demeaning the EPU series under either two or four mean level shifts.

D Additional Tables

Table D1. VAR lag order

	Standard linear trend	Structural shifts detrending 2 EPU level shifts	Structural shifts detrending 4 EPU level shifts
2 - VAR	5	5	5
3 - VAR	4	4	4
4 - VAR	2	2	2
5 - VAR	4	4	4

The optimal number of lags for each VAR(p) model is chosen based on the standard information criteria and the elimination of serial correlation from the residuals.

Table D2a. 5 -VAR DPR causality results - standard linear trend included

	Predicted				
p=2 lags	EPU	DJIA	EFFR	EMP	IP
Predictor					
EPU		$1, 2^{(**)}$	$1-7$	$4, 6^{(**)}$	$1-2^{(**)}$
DJIA	$1-4, 7$			$6-7$	$1-7$
EFFR		$3^{(**)}$			$1-2^{(**)}$
EMP	$1, 6, 7$				$1-6$
IP	$1-3^{(**)}, 5^{(**)}$	$1-2, 3^{(**)}, 5^{(**)}$	$1-7$	$1-7$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 7$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table D2b. 5 -VAR DPR causality results - structural shifts in linear trend included: 2 level shifts in EPU

	Predicted				
p=4 lags	EPU	DJIA	EFFR	EMP	IP
Predictor					
EPU		$1-5, 6^{(**)}, 7, 8^{(**)}$	$1-12, 13^{(**)}$		
DJIA	$1-2, 3-4^{(**)}$		4	$2^{(**)}, 3-11,$ $12-13^{(**)}$	$1, 2-3^{(**)}, 4$
EFFR	$7-8^{(**)}$	$1-10, 12^{(**)}, 13$			
EMP	$8^{(**)}, 9, 12$		$1^{(**)}$		
IP	$6^{(**)}, 7, 8^{(**)}, 13$	$1^{(**)}, 3-9, 11^{(**)}$	$4-5^{(**)}, 6-9,$ $10-12^{(**)}, 13$	$1-5, 6^{(**)}$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 13$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table D2c. 5 -VAR DPR causality results - structural shifts in linear trend included: 4 level shifts in EPU

	Predicted				
p=4 lags	EPU	DJIA	EFFR	EMP	IP
Predictor					
EPU		$1-8$	$1-3, 4-5^{(**)}$		
DJIA	$1-2$		$4^{(**)}$	$4-11, 13^{(**)}$	$1-4, 5-6^{(**)}$
EFFR	$6-9$	$1-10, 11-12^{(**)}, 13$		$8-13^{(**)}$	
EMP	12		$1^{(**)}$		
IP	$7, 13$	$1^{(**)}, 5-9, 10-11^{(**)}$	$5-6^{(**)}, 7-8,$ $9^{(**)}, 12^{(**)}, 13$	$1-5$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 13$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

Table D3. 6 -VAR DPR causality results - standard linear trend included

	Predicted					
p=4 lags	VXO	EPU	S&P500	EFFR	EMP	IP
Predictor						
VXO				$1-5, 6^{(**)}, 7-11, 12^{(**)}, 13, 14-16^{(**)}$	$4-5$	$1^{(**)}$
EPU				$1-2, 3-4^{(**)}, 5-17$	$1-3^{(**)}$	
S&P500		$1-2^{(**)}$			$4-5, 14^{(**)}, 15, 16^{(**)}$	$1-16, 17^{(**)}$
EFFR	$-$	$-$	$-$	$-$	$-$	$-$
EMP		$8^{(**)}, 9-10, 11^{(**)}$		$1-2^{(**)}, 4-5^{(**)}$		
IP	$1^{(**)}$		1	$1, 2-4^{(**)}, 5-13, 14-15^{(**)}$	$1-7, 8-10^{(**)}, 13^{(**)}, 14, 15^{(**)}, 16-17$	

Notes. The null hypothesis is that the "predictor" does not cause the "predicted" variable at horizon $h = 1, \ldots, 17$. Reported horizons signify cases in which the null hypothesis of non-causality is rejected at the 5% and the 10% (cases with **) significance level.

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