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Stravos Degiannakis and George Filis

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Stavros Degiannakis[1,2] and George Filis[3,*]

[1]Department of Economics and Regional Development, Panteion University of Social and Political Sciences, 136 Syggrou Avenue, 17671, Greece.
[2]Postgraduate Department of Business Administration, Hellenic Open University, Aristotelous 18, 26 335, Greece.
[3]Department of Accounting, Finance and Economics, Bournemouth University, 89 Holdenhurst Road, BH8 8EB, Bournemouth, UK

*Corresponding author: email: gfilis@bournemouth.ac.uk

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Abstract

Forecasting the economic policy uncertainty in Europe is of paramount importance given the on-going debt crisis and the Brexit vote. This paper evaluates monthly out-of-sample economic policy uncertainty index forecasts and examines whether ultra-high frequency information from asset market volatilities and global economic policy uncertainty can improve the forecasts relatively to the no-change forecast. The results show that the global economic policy uncertainty provides the highest predictive gains, followed by the European and US stock market volatilities. The results hold true even when we consider the directional accuracy.

Keywords: Economic policy uncertainty, forecasting, financial markets, commodities markets, HAR, ultra-high frequency information.

JEL: C22, C53, E60, E66, G10.

1. Introduction

Although the effects of policy uncertainty on economic conditions have attracted the interest of academic research for over 35 years (see, for instance, Marcus, 1981; Bernanke, 1983; Colombo, 2013), such interest has reemerged since the Global Financial Crisis of 2007-2009, the European debt crisis since 2010, as well as, more recently with the Trump's win in the US elections and the UK's referendum vote for Brexit (Antonakakis *et al*., 2013; New York Times, 2016; Bloomberg, 2017; Caggiano, 2017).

The economic uncertainty is a key determinant of the business cycle and its effects on economic activity is mainly propagated either through household consumption decisions and delays in firms' hiring plans or via delays in the investment activity in physical capital (Visco, 2017). More specifically, households tend to postpone spending and increase their precautionary savings when there is uncertainty surrounding monetary and fiscal policy decisions. Along a similar vein, when economic policy uncertainty is high, firms postpone their investment plans, given the irreversibility of such decisions (Pindyck, 1990), which results in lower productivity and higher levels of unemployment (Bloom, 2009; Bloom *et al*., 2012; Bloom, 2014). Kang *et al*. (2014) second these findings, arguing further that when the real sector is faced with uncertainty regarding future decisions in terms of health care costs, tax codes or changes in regulations, then it tends to delay investment plans. Such effects are particularly evident during recession periods.

Despite the importance of economic policy uncertainty in economic developments, there is no effort (so far) to forecast it, so to allow policy makers and economic agents to act upon such forecasts. By contrast, recent studies have only tried to examine the predictive content of economic policy uncertainty on either US recessions (Karnizova and Li, 2014) or stock market volatility (Liu and Zhang, 2015).

Even more, there is a strand in the literature showing that economic policy uncertainty is not only related to monetary and fiscal decisions, but it is also impacted by financial and commodities markets. For instance, Beckmann and Czudaj (2017) show that there is a link between exchange rate expectations and economic policy uncertainty. Furthermore, studies show that changes in oil price shocks or stock market volatility trigger changes in economic policy uncertainty (Antonakakis *et al*., 2013, 2014; Kang and Ratti, 2013). Hence, we maintain that asset volatilities might contain important predictive information for the economic policy uncertainty.

Thus, this paper aims to fill this void and assesses whether asset volatilities provide predictive gains on European economic policy uncertainty index (developed by Baker *et al*., 2016) forecasts. We choose to focus in Europe, due to the ongoing debt crisis, as well as, the Brexit vote.

The rest of the paper is structured as follows. Section 2 describes the data used and Section 3 outlines the forecasting models. Section 4 provides an analysis of the findings and Section 5 concludes the study.

2. Data Description

In this study we employ monthly data from Baker *et al*. (2016) European economic policy uncertainty (EPU) index, as well as, tick-by-tick front-month futures contracts data of two major European stock market indices (FTSE100 and Eurostoxx 50) and two major currencies (GBP/USD and EUR/USD). We further consider whether global economic conditions and asset markets could also provide predictive information to the EPU forecast. Thus, tick-by-tick front-month futures contracts of the S&P500 stock index, Brent crude oil and US 10yr T-bills and monthly data from the Global EPU are also used in this study. The tick-by-tick data are used to construct monthly realized volatilities for the aforementioned assets (see Appendix 1 for the technical details). Table 1 presents the data used in the study.

[TABLE 1 HERE]

The period of our study spans from August, 2003 to August, 2015 and it is dictated by the availability of intraday data for the Brent Crude oil futures contracts. Table 2 presents the descriptive statistics of the series.

[TABLE 2 HERE]

We show that EPU and GEPU are very volatile, relatively to the volatilities of the remaining asset classes. Furthermore, the Brent crude oil exhibits the higher average volatility compared to the remaining assets, as well as, the highest standard deviation, followed by the Eurostoxx 50 and FTSE100 volatilities. By contrast, the lowest volatilities are associated with the US T-bill and the two currencies of our series. Finally, all variables exhibit non-normality, as suggested by the Jarque-Bera test, skewness and kurtosis.

4. Forecasting models

We should highlight here again that economic policy uncertainty has not been forecasted before, and thus we need to select a model that is well established in the literature of being able to successfully forecast uncertainty. The financial literature has shown that Corsi's (2009) Heterogeneous AutoRegressive model is capable of modelling and forecasting financial uncertainty, as approximated by asset price realized volatility (see, *inter alia*, Andersen *et al*., 2007). Hence, we maintain that this is an appropriate framework for modelling and forecasting economic uncertainty. Degiannakis and Filis (2017) further proposed the HAR-X model incorporating information from exogenous assets. In our case, the HAR-X model for the EPU_t is employed for monthly data in the form:

$$\begin{gathered} log(EPU_t) = \\ w_0 + w_1 log(EPU_{t-1}) \ + w_2\left(3^{-1}\sum_{k=1}^{3} log(EPU_{t-k})\right) + \\ w_3\left(12^{-1}\sum_{k=1}^{12} log(EPU_{t-12})\right) + w_4 log\left(RV_{x,t-1}^{(M)}\right) \ + w_5\left(3^{-1}\sum_{k=1}^{3} log\left(RV_{x,t-k}^{(M)}\right)\right) + \\ w_6\left(12^{-1}\sum_{k=1}^{12} log\left(RV_{x,t-k}^{(M)}\right)\right) + \varepsilon_t, \end{gathered} \tag{1}$$

where ε_t is a white noise and $RV_{x,t-k}^{(M)}$ denotes the monthly realized volatility of the exogenous asset for $t-k$ month. When the Global EPU is the exogenous variable, the $RV_{x,t-k}^{(M)}$ is replaced with $GEPU_{t-k}$. The proposed HAR-X model incorporates information of the previous month's, quarters' and year's EPU_t and $RV_{x,t-k}^{(M)}$. Thus, the summation of uncertainly measure and realized volatility at different time horizons accommodates the volatility persistence and long-memory behavior detected in financial markets.

Apart from the HAR-X models, we further estimate the no-change forecast, an AR(1) model and a simple HAR model without any exogenous variable, which are used as benchmarks.

5. Empirical analysis

The out-of-sample forecasting ability of the competing models is gauged using two standard loss functions, namely the mean squared predictive error (MSPE) and the mean absolute percentage predictive error (MAPPE). Results are shown in Tables 3 and 4.

[TABLE 3 HERE]

[TABLE 4 HERE]

Tables 3 and 4 report the predictive gains of the competing models relatively to the no-change forecast (random walk). From these results it is clear that there is not a single model that outperforms all others at all forecasting horizons. Although, most HAR-X models seem to outperform not only the no-change forecast, but also the AR(1) and the simple HAR model.

More specifically, in the first two months of the out-of-sample forecasts we notice that the HAR-FT, HAR-XX, HAR-SP and HAR-TY are the models, which demonstrate the highest predictive ability. Nevertheless, the HAR-GEPU is the best performing model for all out-of-sample forecasting horizons after the 3-months ahead. In particular, the HAR-GEPU model provides significant predictive gains, as it improves the no-change forecast between 66% and 82% (approximately), based on the MSPE (depending on the forecasting horizon). Interestingly enough, the European exchange rate volatilities do not provide any predictive information and the same holds for the HAR-CO model. More specifically, even though these models perform better than the no-change forecast in the short run (e.g. 1-month to 5-months ahead), they are not able to outperform the AR(1) and HAR. In the longer run forecasting horizons the forecasts of the HAR-BP, HAR-EC and HAR-CO are becoming even worse, as they are not able to outperform the random walk forecasts.

Overall, these findings show that EPU is mainly impacted by the global economic policy uncertainty, as well as, the uncertainty surrounding the financial markets (either European or US/Global). By contrast, the exchange rate market and the leading commodity market (Brent crude oil) do not contain any predictive information.

Following the assessment of the forecasting accuracy of the HAR-X models, we assess their directional accuracy (Table 5). For brevity, Table 5 only considers the best performing models from Tables 3 and 4.

[TABLE 5 HERE]

From Table 5 it is evident that the HAR-GEPU model is able to provide a materially high directional accuracy, which ranges between 60.61% and 78.79%. This does not hold for the 1-month ahead forecasting horizons where the directional accuracy of the HAR-GEPU model is only 51.52%. Importantly, the model which also demonstrates a very high directional accuracy is the HAR-SP model, although this model was not ranked that high in terms of forecasting accuracy.

These results suggest that the HAR-X models which are augmented with the stock market volatilities and GEPU should be used by policy makers or users who are interested in the accuracy of the forecasts, whereas those stakeholders who are mainly interested in the direction of the EPU index should not take under consideration the informational content of the European stock market volatilities.

6. Conclusion

This paper forecasts for the first time the European economic policy uncertainty index, using information from European and global asset market volatilities, as well as, the global economic policy uncertainty. The results show that the latter offers significant predictive gains, ranging between 66% and 82%, compared to the no-change out-of-sample forecasts. In addition, the information extracted from the stock market volatilities provides materially high predictive gains for the European economic policy uncertainty index. These results also hold when we consider the directional accuracy of these models. These results are important for policy makers who aim to maintain economic policy uncertainty at low level so to avoid reduced consumer spending and firms' underinvestment. For instance, when financial volatility, either from Europe or the US, increases, then this should alarm policy makers that the economic policy uncertainty will follow suit in the following months, allowing them to be proactive rather than reactive. Finally, our findings highlight that this is a very important line of research which deserves significant more attention.

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Table 1: Variables' description and sources.

Name	Acronym	Description	Source
		Variable to be forecasted	
European Economic Policy Uncertainty Index	EPU	Proxy for the European macroeconomic volatility	Baker *et al*. (2016)
		European related exogenous variables	
FTSE100 index	FT	Tick-by-tick data of the front-month futures prices	TickData
Euro Stoxx 50 index	XX	Tick-by-tick data of the front-month futures prices	TickData
GBP/USD exchange rate	BP	Tick-by-tick data of the front-month futures prices	TickData
EUR/USD exchange rate	EC	Tick-by-tick data of the front-month futures prices	TickData
		Global related exogenous variables	
Brent Crude Oil	OP	Tick-by-tick data of the front-month futures prices	TickData
S&P500 index	SP	Tick-by-tick data of the front-month futures prices	TickData
US 10yr T-bills	TY	Tick-by-tick data of the front-month futures prices	TickData
Global Economic Policy Uncertainty Index	GEPU	Proxy for the Global macroeconomic volatility	Baker *et al*. (2016)

Table 2: Descriptive statistics (August, 2003 - August, 2015).

	EPU	FT	XX	BP	EC	CO	SP	TY	GEPU
Mean	1.3603	0.1656	0.2043	0.0901	0.0946	0.2834	0.1550	0.0732	1.0557
Maximum	3.0460	0.5919	0.6183	0.2999	0.2492	0.9243	0.5914	0.2842	2.1705
Minimum	0.4769	0.0525	0.0699	0.0292	0.0349	0.0667	0.0443	0.0255	0.5350
Std. Dev.	0.5350	0.0890	0.0909	0.0388	0.0384	0.1403	0.0896	0.0441	0.3863
Skewness	0.5536	2.0757	1.5349	1.9950	1.4907	1.5792	1.9947	1.9427	0.8075
Kurtosis	2.7479	8.5856	6.1548	9.6136	5.6034	6.5610	8.3326	7.4817	3.0385
Jarque-Bera	7.7904	292.6188	117.0672	360.4404	94.6537	136.8825	267.9607	212.5586	15.7655
Probability	0.0203	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004

Note: EPU = European economic policy uncertainty, FT = FTSE100 volatility, XX = EUROSTOXX 50 volatility, BP = GBP/USD volatility, EC = EUR/USD volatility, CO = Brent crude oil price volatility, SP = S&P500 volatility, TY = US T-bill volatility, GEPU = Global economic policy uncertainty.

Table 3: Forecast evaluation of monthly European Economic Policy Uncertainty based on the MSPE. Evaluation period: December, 2011 - August, 2015.

Forecasting Horizon	RW	AR(1)	HAR	HAR-FT	HAR-XX	HAR-BP	HAR-EC	HAR-CO	HAR-SP	HAR-TY	HAR-GEPU
					MSPE ratio						
1	**5144.09**	**0.1858**	**0.1580**	**0.1470**	**0.1566**	**0.2016**	**0.2654**	**0.1746**	**0.1586**	**0.1432**	**0.1737**
2	**4880.82**	**0.3001**	**0.2205**	**0.2203**	**0.2141**	**0.3063**	**0.4036**	**0.2629**	**0.2281**	**0.2147**	**0.2261**
3	**4777.60**	**0.3802**	**0.2453**	**0.2328**	**0.2287**	**0.3774**	**0.4984**	**0.3109**	**0.2411**	**0.2536**	**0.2190**
4	**4775.07**	**0.4612**	**0.2574**	**0.2474**	**0.2453**	**0.4084**	**0.5960**	**0.3560**	**0.2409**	**0.2508**	**0.1999**
5	**4832.12**	**0.5330**	**0.2574**	**0.2422**	**0.2306**	**0.4557**	**0.7216**	**0.3893**	**0.2313**	**0.2437**	**0.1736**
6	**4714.48**	**0.5867**	**0.2785**	**0.2535**	**0.2341**	**0.5632**	**0.9475**	**0.4512**	**0.2497**	**0.2622**	**0.1855**
7	**4482.25**	**0.6501**	**0.3457**	**0.2887**	**0.2624**	**0.7205**	**1.2933**	**0.5824**	**0.2952**	**0.2840**	**0.2311**
8	**4165.94**	**0.7047**	**0.4267**	**0.3270**	**0.2966**	**0.9697**	**1.7610**	**0.7454**	**0.3489**	**0.3179**	**0.2818**
9	**4067.91**	**0.7407**	**0.4676**	**0.3377**	**0.3066**	**1.1812**	**2.2674**	**0.8339**	**0.3829**	**0.3537**	**0.2884**
10	**4187.19**	**0.7898**	**0.4853**	**0.3356**	**0.2957**	**1.2525**	**2.6567**	**0.8792**	**0.3692**	**0.3471**	**0.2523**
11	**4066.16**	**0.8186**	**0.5677**	**0.4048**	**0.3418**	**1.6345**	**3.5655**	**1.0392**	**0.4380**	**0.4033**	**0.2899**
12	**3878.64**	**0.8550**	**0.7146**	**0.5075**	**0.4188**	**2.3234**	**5.1534**	**1.3069**	**0.5516**	**0.5215**	**0.3369**

Note: All MSPE ratios have been normalized relative to the no-change forecast. The RW (Random-Walk) model values refer to the actual MSPE. Moving from the light green towards the dark red colour, denotes movement from the best towards the worse model. FT = FTSE100 volatility, XX = EUROSTOXX 50 volatility, BP = GBP/USD volatility, EC = EUR/USD volatility, CO = Brent crude oil price volatility, SP = S&P500 volatility, TY = US T-bill volatility, GEPU = Global economic policy uncertainty.

Table 4: Forecast evaluation of monthly European Economic Policy Uncertainty based on the MAPPE. Evaluation period: December, 2011 - August, 2015.

Forecasting Horizon	RW	AR(1)	HAR	HAR-FT	HAR-XX	HAR-BP	HAR-EC	HAR-CO	HAR-SP	HAR-TY	HAR-GEPU
		MAPPE ratio									
1	**30.89%**	**0.4494**	**0.4409**	**0.4188**	**0.4237**	**0.4938**	**0.5399**	**0.4690**	**0.4194**	**0.4299**	**0.4543**
2	**30.17%**	**0.5414**	**0.5202**	**0.5232**	**0.5155**	**0.5804**	**0.6698**	**0.5592**	**0.5309**	**0.5139**	**0.5174**
3	**29.92%**	**0.5649**	**0.5819**	**0.5524**	**0.5466**	**0.6657**	**0.7547**	**0.6588**	**0.5644**	**0.5708**	**0.5178**
4	**29.78%**	**0.6584**	**0.5896**	**0.5584**	**0.5505**	**0.7082**	**0.8071**	**0.7077**	**0.5642**	**0.5734**	**0.5091**
5	**29.75%**	**0.6947**	**0.6174**	**0.5556**	**0.5523**	**0.7694**	**0.9382**	**0.7903**	**0.5801**	**0.5674**	**0.4967**
6	**29.44%**	**0.7630**	**0.6388**	**0.6009**	**0.5763**	**0.8166**	**1.0901**	**0.8125**	**0.6103**	**0.6040**	**0.5124**
7	**29.00%**	**0.7672**	**0.7061**	**0.6352**	**0.5929**	**0.9329**	**1.2716**	**0.9557**	**0.6419**	**0.6250**	**0.5699**
8	**28.50%**	**0.8069**	**0.7838**	**0.6899**	**0.6575**	**1.0714**	**1.4713**	**1.0699**	**0.7049**	**0.6731**	**0.6145**
9	**28.18%**	**0.8548**	**0.8130**	**0.6922**	**0.6511**	**1.1866**	**1.6609**	**1.1552**	**0.7236**	**0.7003**	**0.6108**
10	**28.36%**	**0.8675**	**0.8490**	**0.6953**	**0.6580**	**1.2323**	**1.8015**	**1.1949**	**0.7349**	**0.7088**	**0.6029**
11	**27.99%**	**0.8734**	**0.8980**	**0.7592**	**0.6989**	**1.3617**	**2.0713**	**1.2905**	**0.7937**	**0.7525**	**0.6520**
12	**27.55%**	**0.9139**	**1.0268**	**0.8414**	**0.7723**	**1.6211**	**2.4978**	**1.4330**	**0.8882**	**0.8495**	**0.6965**

Note: All MAPPE ratios have been normalized relative to the no-change forecast. The RW (Random-Walk) model values refer to the actual MAPPE. Moving from the light green towards the dark red colour, denotes movement from the best towards the worse model. FT = FTSE100 volatility, XX = EUROSTOXX 50 volatility, BP = GBP/USD volatility, EC = EUR/USD volatility, CO = Brent crude oil price volatility, SP = S&P500 volatility, TY = US T-bill volatility, GEPU = Global economic policy uncertainty.

Table 5: Success ratio of the best competing models. Evaluation period: 2011.12-2015.8.

Forecasting Horizon	HAR-FT	HAR-XX	HAR-SP	HAR-TY	HAR-GEPU
1	**0.6364**	**0.6364**	**0.6970**	**0.6667**	**0.5152**
2	**0.5758**	**0.5758**	**0.6061**	**0.5152**	**0.6061**
3	**0.5455**	**0.5455**	**0.6061**	**0.5455**	**0.6364**
4	**0.6061**	**0.6061**	**0.6061**	**0.6061**	**0.6061**
5	**0.6364**	**0.6061**	**0.6061**	**0.6364**	**0.6061**
6	**0.5758**	**0.5758**	**0.6364**	**0.5758**	**0.6667**
7	**0.6061**	**0.6667**	**0.6364**	**0.5455**	**0.6667**
8	**0.6667**	**0.6364**	**0.6667**	**0.6667**	**0.6667**
9	**0.6667**	**0.6667**	**0.7273**	**0.6364**	**0.7879**
10	**0.6364**	**0.6364**	**0.6667**	**0.6970**	**0.7273**
11	**0.6364**	**0.6970**	**0.6364**	**0.6364**	**0.6970**
12	**0.6667**	**0.6970**	**0.6970**	**0.6364**	**0.6970**

Note: Moving from the light green towards the dark red colour, denotes movement from the best towards the worse model. FT = FTSE100 volatility, XX = EUROSTOXX 50 volatility, SP = S&P500 volatility, TY = US T-bill volatility, GEPU = Global economic policy uncertainty.