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Does economic policy uncertainty affect stock market returns in Sweden?

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Abstract: Earlier studies have shown that Economic Policy Uncertainty (EPU) in the US affects different macroeconomic and financial variables in the US and in various European countries, among them Sweden. The relationship between EPU in Sweden (a novel index) and the stock market in Sweden have not been studied. Using a Vector Autoregressive approach, I find that lags of stock market returns in Sweden Granger cause Swedish EPU. The direction of causality is the opposite of what was hypothesized.

Keywords:	policy uncertainty, economic uncertainty, stock market returns, Sweden, VAR, Granger causality
JEL Classification:	C32, D80, E66, G18
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1 Introduction

“Uncertainty is an uncomfortable position.
But certainty is an absurd one.”

– Voltaire

In the political debate, by journalists and experts, we are often told that the political climate have not been as tense since the Cold War. Tension and uncertainty prevail both domestic politics (e.g. the rise of right-wing extremism) as well as international relations (Brexit, the war in Syria, relations with North Korea etc.). To say that different kinds of uncertainties have large impacts on financial markets as well as the overall economy is not controversial. In this paper, I will study uncertainty related to economic policy and its relation to the stock market in Sweden, using the Economic Policy Uncertainty (EPU) index.

A theoretical model for the relationship between the stock market and economic policy uncertainty has been proposed by Pástor and Veronesi (2013). According to this model, in times of high economic policy uncertainty, the stock market ought to be more volatile and the risk premium should be higher, but this effect should be smaller and less noticeable in a strong economy. Other empirical studies have confirmed a relationship between US EPU and US stock market returns as well as US EPU and stock returns in Sweden and other European countries. Studies on the relationship between the Swedish economic policy uncertainty index and stock returns in Sweden have not been conducted, however. To fill this empirical gap, my research question will be:

Does domestic economic policy uncertainty affect stock market returns in Sweden?

My hypothesis is that lags of economic policy uncertainty in Sweden will affect stock market returns negatively in accordance with research for other countries. However, the reverse direction of causality could also be the case, since a stock market that is volatile or has abnormal returns could lead to uncertainty regarding what policy makers will do, for example in times of recession where the stock market behaves differently and policy makers might react or be expected to react to this. A third alternative could be that policy uncertainty affect the stock market and that the stock market affect policy uncertainty. Wisniewski (2016) discusses this possibility and calls it a "bi-directional feedback loop". Of earlier theoretical explanations, a number of them have not captured this. He consequently suggests more research on this potential feedback loop. Furthermore, Pástor and Veronesi (2013)'s model suggest that the effect is smaller for a stronger economy, and Sweden's strong economy (especially in recent years) may make this effect negligible.

The connection between the Swedish EPU index and stock market returns will examined using a Vector Autoregressive (VAR) approach where I estimate a model of how lags of the time series Swedish EPU and SIXRX (an index for stock market development in Sweden) affect each other, without making an a priori assumption regarding direction of causality. Thereafter, I will test for Granger causality. The reason for me to chose to study if lags of EPU affects stock market returns and not to study a contemporaneous effects is that in order to have contemporaneous terms in a VAR, one has to make an a priori assumption about the direction of causality due to the econometric properties of a VAR. I do not want to do this, thusly I only study a non-contemporaneous effect, that is, how lags of one variable affects the other.

According to my findings, there is a negative relationship between stock market returns in Sweden and the Swedish EPU index, but I find that stock returns Granger cause Swedish EPU and not the opposite. After several post estimation tests, I come to the conclusion that my results are robust. This is discussed further in this thesis.

Though the EPU index for different countries have been used by both academics and professionals for years, the index for Sweden was created only last year by Armelius, Hull and Köhler (2017). To my knowledge, no papers have been published on the Swedish index except the original paper, where the index is compared to GDP growth and other macro variables in Sweden as well as the EPU index for other countries, but no variables related to the stock market. The Swedish EPU index do correlate with the indices for the US and Europe as a whole, but not very strongly (see Table 1 and Figure 1). Consequently, the Swedish index is interesting to study by itself.

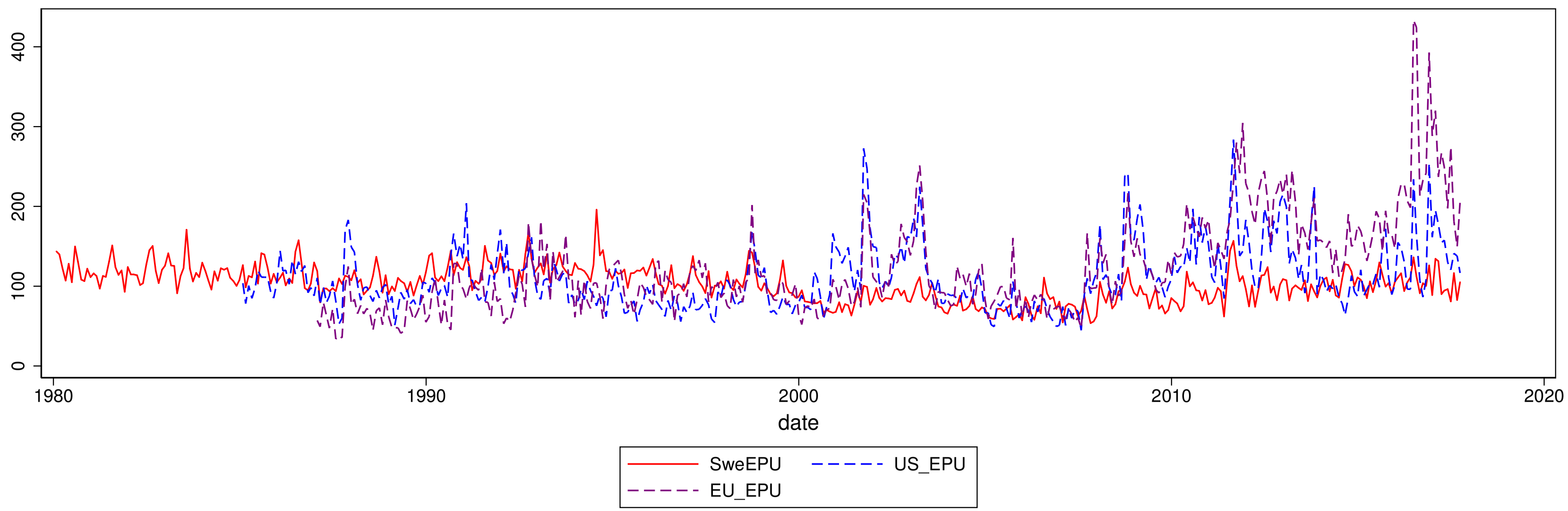

Figure 1: Swedish EPU in comparison with EPU for USA and Europe over time.

Table 1: Correlation coefficients for the Swedish, US and European EPU indices. The time series compared are on a monthly basis. Since EU EPU was only available from January 1987, all observations before that were dropped for Swedish EPU and US EPU.

	SweEPU	US EPU	EU EPU
SweEPU	1.0000		
US EPU	0.2329	1.0000	
EU EPU	0.1579	0.6567	1.0000

Further knowledge of this novel index and its connection to financial variables is of interest to various stakeholders. Not only do economists and financial economists want to understand what affects macro variables and financial markets, but also financial professionals benefit from increased knowledge on this topic, such as fund managers, equity research divisions etc. The European EPU index is used by financial analysts by for example Deutsche Bank Research (Deutsche Bank, 2018). Researchers in other disciplines could also benefit, such as political scientists. In addition, other agents might utilize such knowledge, e.g. politicians who estimate the effects of their decisions, private investors or ordinary citizens who are affected by political decisions and uncertainty.

Moreover, Sweden is an interesting country to study with regards to policy uncertainty even if one is not interested in issues specifically related to Sweden, mainly for it being a small open economy while most other studies are conducted on US data. Also, Sweden's economy has historically been very strong, which is interesting, since for example Wisniewski (2016) have concluded that the effect of politics and uncertainty is larger for emerging markets than for more developed economies. Hence my paper will hopefully contribute to further understanding of the relationship between economic policy uncertainty in Sweden and the development of the stock market, as well as understanding of economic policy uncertainty in general.

2 Literature review

There has been a rich and broad literature on uncertainty. Hereinafter, I will go through this literature, and narrow it down to economic policy uncertainty and evidence of its connection to other economic variables. But first, the general concept of uncertainty is discussed.

Uncertainty can simply be explained as the lack of certainty. Uncertainty is not the same as risk. Knight (1921) makes this distinction by saying that risk is something you can estimate and thus quantify with more information, while uncertainty is impossible to calculate. One simply cannot know anything about the state of this part of the universe. To overcome this problem of not being able to quantify, scholars have instead created indices or other proxies for uncertainty in order to incorporate it in empirical research.

If looking at the empirical research of uncertainty, it seems that times of high uncertainty tend to lead to higher stock market volatility. Białkowski, Gottschalk and Wisniewski (2008) find that elections drive stock market volatility by studying a large sample of countries. This increased volatility seem to be incorporated in asset prices, since for example Pantzalis, Stangeland and Turtle (2000) find that stock market returns tend to be abnormally high the weeks before elections. Hence, uncertainty is an interesting concept when studying the stock market, and hereinafter this paper will focus on economic policy uncertainty.

Economic Policy Uncertainty is simply uncertainty regarding economic policy, such as the central bank's interest rate, taxation or other monetary and fiscal policy issues. Due to the immense effect of economic policy on firms, the financial sector and the economy as whole, such uncertainty is obviously interesting to study. Baker, Bloom and Davis (2016)[1] created an index for economic policy uncertainty in the US using scraping. This means counting articles containing certain words that express economic policy uncertainty in ten of the largest newspapers in the US[2]. Examples of such words are "White House", "regulation" and "deficit". As

[1]The same article was published as working papers in 2011 and 2013, hence it is cited by articles published earlier than 2016.

[2]The newspapers currently included are USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle,

expected, the index spikes around macro events that are associated with a large degree of uncertainty, such as presidential elections and the crisis of 2007-2008 and 9/11 (see Figure 2). Baker et al. also created indices for other countries using the same methodology, among them Russia, India, UK and Germany. Later on, EPU indices for other countries and areas (such a global index and a European index) were created (*Economic Policy Uncertainty Index*, 2018).

Last year, Armelius et al. (2017), developed an EPU index for Sweden (hereby called SweEPU) using the same methodology, scraping articles from the Swedish newspapers Aftonbladet, Expressen, Dagens Industri and Svenska Dagbladet for words associated with uncertainty regarding economic policy, for example the Swedish words “Riksbank”, “reglering” and “oro” (meaning “the central bank”, “regulation” and “uncertainty”). The reader acquinted with Swedish media may wonder why Sweden’s largest newspaper, Dagens Nyheter (DN), is not on the list. I contacted Armelius et al. regarding this. The explanation is that DN’s archives contain gaps that are currently being fixed, so future indices will hopefully include DN.

As mentioned, the Swedish and US EPU indices are not very correlated (Table 1). From correspondence via e-mail from Armelius et al. I got the explanation that they see this as a sign that Sweden has a vast amount of local uncertainty idiosyncratic to Sweden and that this did not penetrate newspapers in the US. To take this reasoning further, one can for example look at the crisis in 2007-2008, where Sweden was not very affected compared to the US and other countries. On that account Sweden’s uncertainty regarding economic policy in recent years should be an outlier in an international context. A sign of this is that the volatility of the Swedish EPU index is substantially lower in the years after 2007 if looking at Figure 1.

Baker et al. empirically showed that US EPU is positively correlated with stock market volatility and negatively correlated with investments in the US. In general, it seems to be that lags of EPU that affects other macro variables. US EPU have also been shown to affect macro variables in other countries, Sweden among them. For example Stockhammar and Österholm (2016) study the effect

the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal.

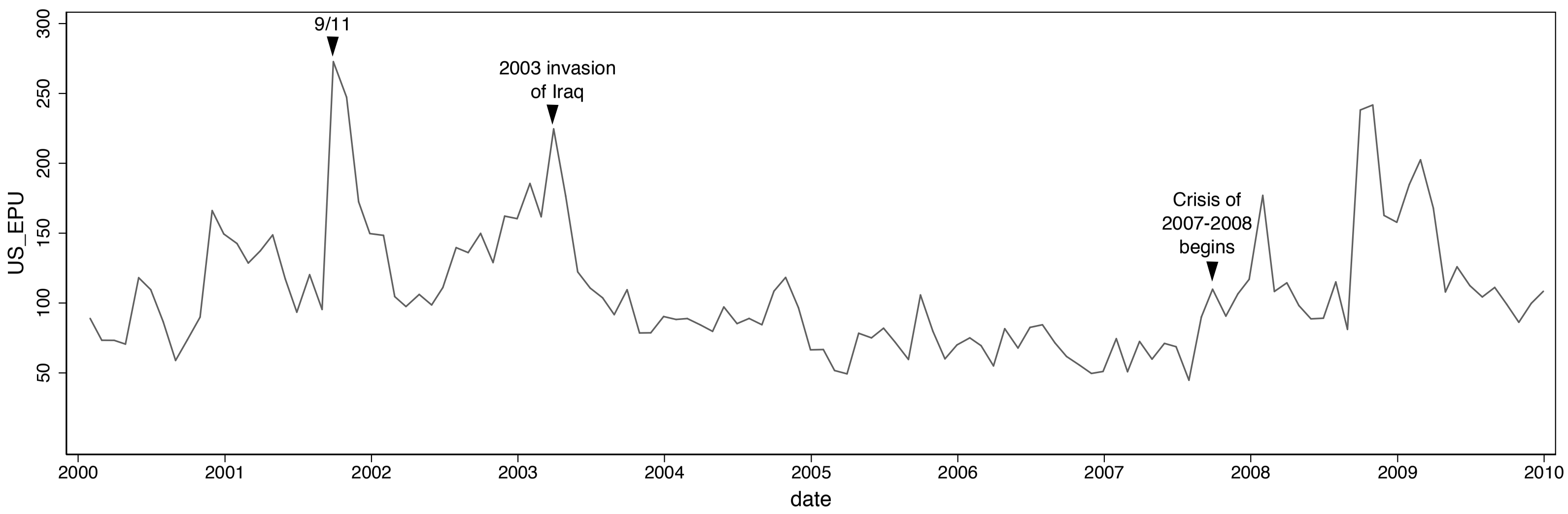

Figure 2: The economic policy uncertainty index (EPU) for the USA during 2000-2010. As one can expect, the index spikes around sudden events and crises. Here a few such events have been marked for comparison.

of US EPU on GDP growth in Sweden. The EPU index has also been used in other studies where its connection to financial markets has been confirmed. Pástor and Veronesi's theoretical general equilibrium model, as described earlier, is one example. They find empirical support for their model using the US EPU index and US stock data. Antonakakis, Chatziantoniou and Filis (2014) find that increased US EPU is associated with lower returns on the American stock market. Sum (2012a, 2012b) show using an OLS approach that US EPU forecasts stock returns in several European countries negatively, among them Sweden. Wisniewski and Lambe (2015) use the index to show that US EPU affects credit default swap spreads (a proxy for firm-specific risk) using a Vector Autoregressive (VAR) framework.

Other than macroeconomic and financial variables, EPU has been used to study for example CSR investments, oil prices, subjective well-being, tourism, performance of financial analysts, R&D (which deviates since R&D correlates positively with uncertainty), M&A, income inequality and unemployment. See for example Antonakakis et al. (2014), Balcilar, Bekiros and Gupta (2017), Tonzer (2017), Gozgor and Ongan (2017), Atanassov, Julio and Leng (2016), Bonaime, Gulen and Ion (2017), Baloria and Mamo (2017) and Husted Corregan and Saffar (2017).

Other measures to proxy for uncertainty have been used. Shoag and Veuger (2016) and Azzimonti (2017) created their own indices using similar techniques as Baker et al. (2016). These are however not made for a long period of time or made with help of more US specific inputs, thus not available for other countries. Others have looked at calculated volatilites of macroeconomic and financial time series using more advanced econometrics to proxy for risk and uncertainty, such as Fernández-Villaverde, Guerrón-Quintana, Kuester and Rubio-Ramírez (2015) and Jurado, Ludvigson and Ng (2015). Both Fernández-Villaverde et al. and Jurado et al. found that their indices correlates well with EPU. Another approach that has been used is using elections to proxy for turbulent times and uncertainty (see for example Białkowski et al. (2008) and Pantzalis et al. (2000)).

The alternatives mentioned above are, however, not as frequently used as EPU. Hence, EPU can be called the standard choice when looking at policy uncertainty. This, in combination with it being available for several countries makes and it being used for multiple purposes it the obvious choice to study in this paper.

Table 2: Descriptive statistics. Both SweEPU and SIXRX are indices hence lack units. Index=100 for December 1995 for SIXRX and the SweEPU index is scaled so that the average between 1985 and 2009 is 100.

stats	SweEPU	SIXRX	Returns of SIXRX
N	453	454	453
mean	102.7893	272.5039	.0143303
sd	21.7878	280.2793	.059557
min	53.73407	3.9367	-.215231
max	195.8634	1130	.2751262
ADF[a]	-9.032**	2.628	-18.107**

[a]Augmented Dickey-Fuller test statistic. The 1 % critical value is -3.444.

3 Data

To conduct the VAR analysis to test if economic policy uncertainty in Sweden affects stock market returns, I have used the Swedish EPU index[3] on a monthly basis and the SIXRX index. Swedish EPU is an index (therefore no unit) which is scaled so that the mean from 1985 to 2009 is 100. The SIXRX index contains all companies listed on the Stockholm Stock Exchange (Nasdaq Stockholm) and shows the returns including dividends. It is the leading index for the Swedish fund market and can consequently be seen as a standard choice when proxying for the development of listed equities in Sweden (SIX Financial Information, 2018). One could have chosen an index where dividends are excluded (such as the OMXS30 index), but that would distort the analysis in times of dividends where trading occurs differently. Monthly data of the SIXRX index was downloaded from Swedish House of Finance's FinBas database for the period December 1979 to September 2017. SIXRX is also an index, hence lacks unit like SweEPU, and December 1995

[3]The index is publicly available at `http://www.policyuncertainty.com/sweden_monthly.html`

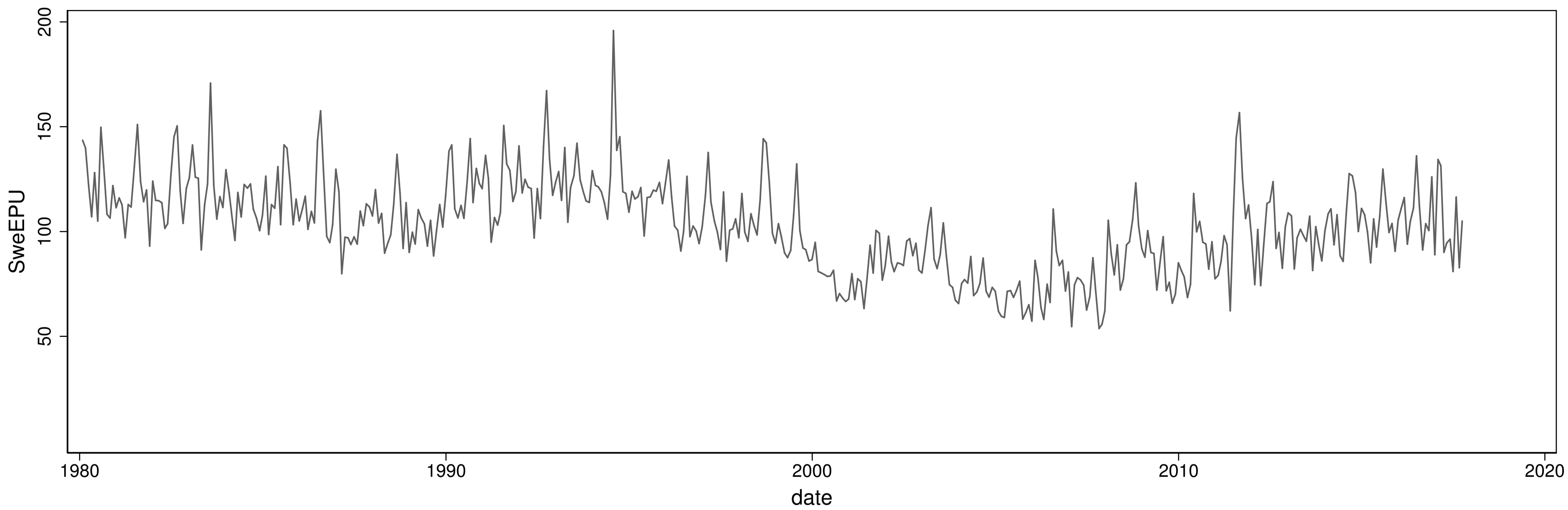

Figure 3: The SweEPU index plotted over time.

is base month (where index is 100) in the data downloaded from FinBas. The same period was used for data of SweEPU. Descriptive statistics for SweEPU and SIXRX can be seen in Table 2. The time series can be seen plotted in Figures 3, 4, 5 and 6.

Regarding if any transformations of my times series ought to be conducted and if so which, I have investigated this rigorously. I will here discuss potential transformation of the data or seasonal adjustment.

In order to infer anything meaningful from a time series it is important ensure that the time series are stationary, otherwise the time series ought to be transformed. A standard approach to test for non-stationarity is to test for a unit root. I have chosen to perform an augmented Dickey-Fuller test on my variables, which can be described as the standard choice for unit-root testing (Brooks, 2008). As can be seen in Table 2, I can reject the presence of a unit root for SweEPU, hence I do not have any reasons to transform the variable and I will use it as it is. This is in accordance with Armelius et al. (2017), who include SweEPU in levels untransformed in their VAR.

SIXRX will be transformed into Returns of SIXRX, calculated as $Returns = \frac{SIXRX_t - SIXRX_{t-1}}{SIXRX_{t-1}}$, since it is the change in the equities' values that are of importance when studying the stock market. In this way, the non-stationarity of SIXRX (Table 2) is not a problem, since Returns of SIXRX are stationary. Consequently, non-stationarity should not impose a problem in the upcoming analysis for neither of the variables included in my VAR.

Regarding seasonal adjustments and de-trending the time series, this is also recommended against in VAR analysis since the time series should be as close to the real-world process in generating the data as possible (Enders, 2008). Thus, such transformations of the data have not been conducted.

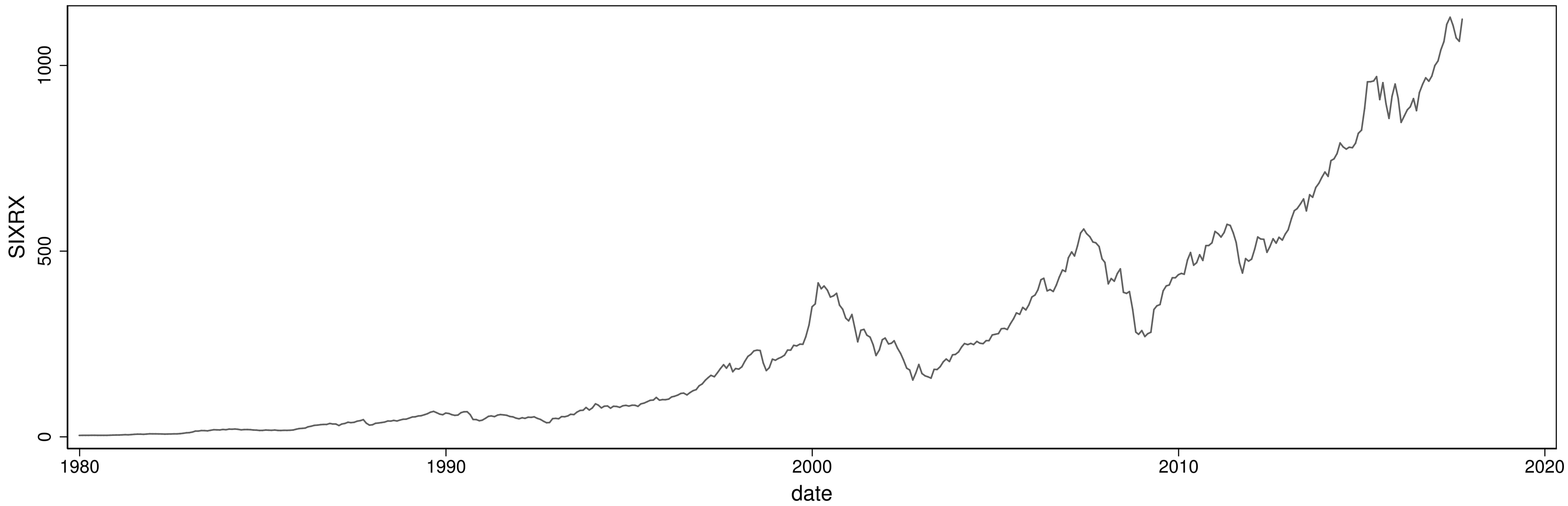

Figure 4: The SIXRX index plotted over time.

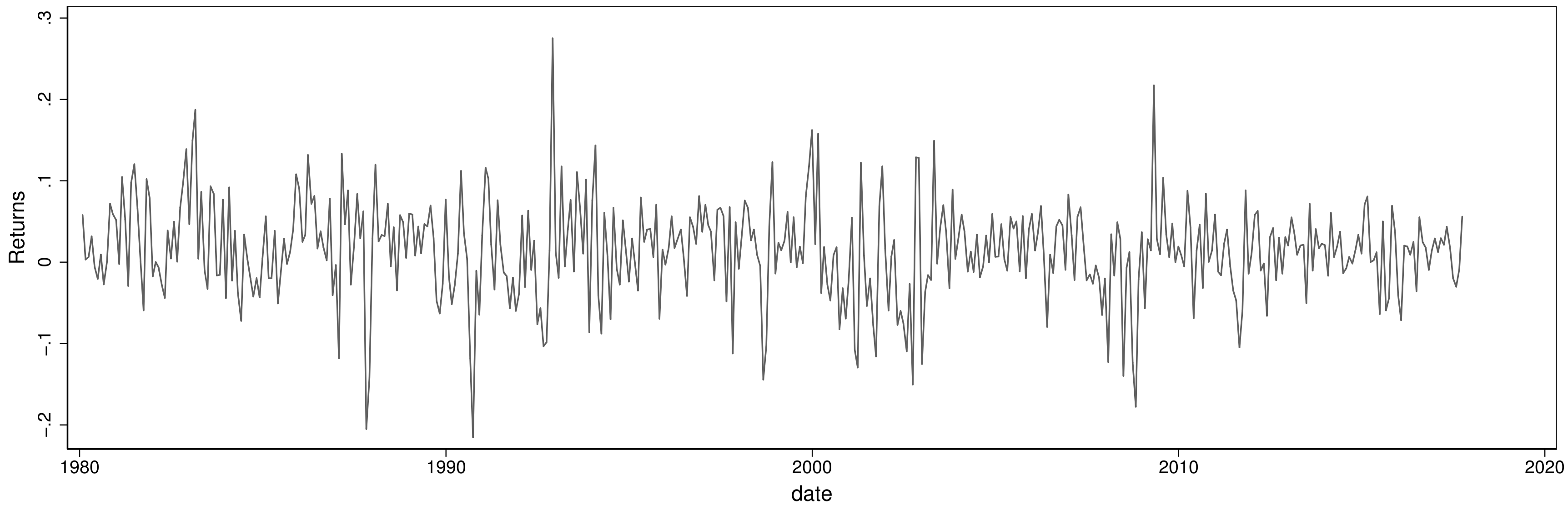

Figure 5: Returns of SIXRX plotted over time.

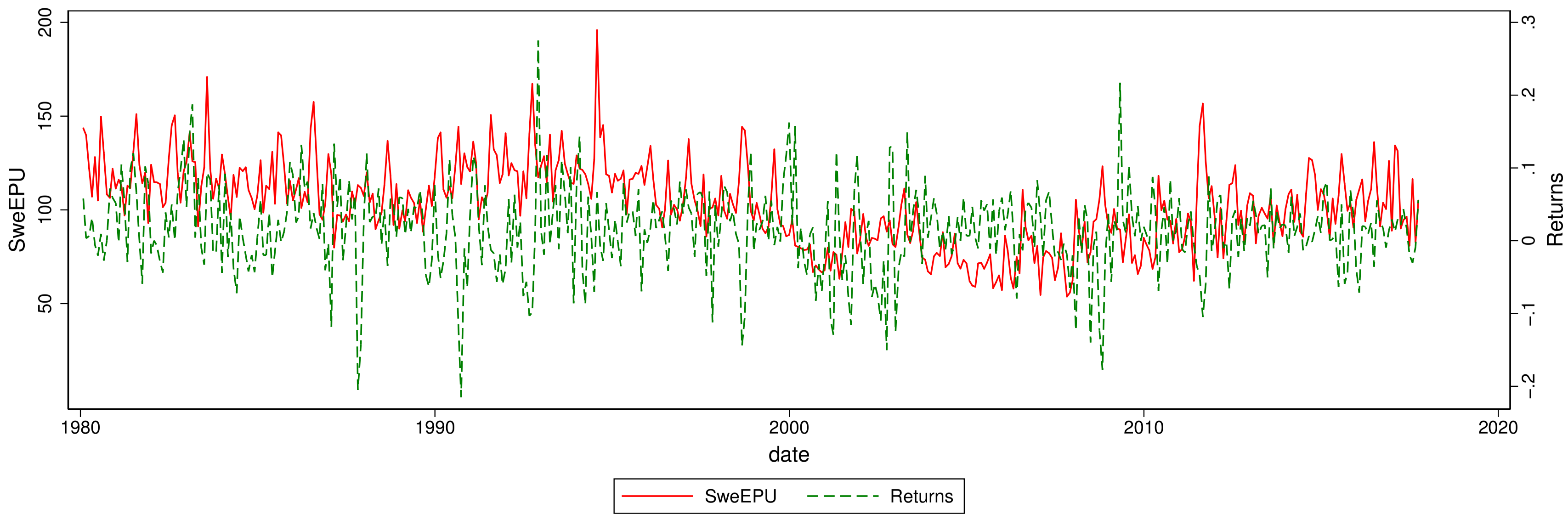

Figure 6: The two time series that will be included in the VAR, SweEPU and returns of SIXRX, plotted in the same graph for comparison.

4 Method

In order to answer the research question, an Vector Autoregressive (VAR) approach will be used. VAR models are currently a popular time series technique in macro applications and have several advantages compared to other time series techniques, most notably the fact that one does not have to assume the direction of causality a priori (Brooks, 2008).

A VAR model does not estimate a single equation like an regular OLS regression does. Instead, an equation system is estimated, that is, we have more than one dependant variable. The independent variables in the regression are lagged values of the independent variable itself and lagged values of the other independent variables in the system (Brooks, 2008). Consider a list of independent variables, time series $y_{1t}, y_{2t}, ...$ denoted as the vector y_t. If we want to estimate a VAR with p lags, then the equation system to be estimated can be written as

$$y_t = c + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{1}$$

with the standard assumptions of u_{it} being errors terms and $E(u_{it}) = 0$ and $E(u_{1t}, u_{2t}, ...) = 0$. A_i are matrices with the estimated coefficients, c is a vector of the estimated intercepts.

There are variants of the VAR model, such as the Structural VAR (SVAR) and Bayesian VAR. SVAR is most commonly used when one has an a priori view of the direction of causality or when one wants to predict policy actions (Enders, 2008), something that does not apply to this paper. Accordingly SVAR will not be used. Bayesian VAR models are more suitable for making predictions by treating the variables as random and can be very useful (Enders, 2008), but this is not what I will be doing in this paper.

Next, I will specify the VAR model by choosing the appropriate number of lags. After the VAR model is estimated, testing for Granger causality will be conducted in order determine if there exist a relationship between Swedish EPU and stock returns and which one affects the other and analysis of impulse response functions will be conducted. The impulse response functions will be orthogonalized (that is, Cholesky decomposition were used in the calculations of the functions) as

Sims (1980) suggest. Another argument for using orthogonalized impulse response functions instead of generalized impulse response functions is that both Armelius et al. (2017) and Stockhammar and Österholm (2016) use orthogonalized impulse response functions, hence I chose this to be consistent with earlier research.

Armelius et al. (2017) and Stockhammar and Österholm (2016) used a bivariate VAR respectively a bivariate Bayesian VAR to examine the relationship between GDP growth in Sweden and Swedish EPU respectively US EPU. I will carry as Armelius et al. did, with a bivariate VAR but examine its relationship with stock returns instead of GDP growth.

When specifying a VAR model, determining the lag length is of importance. From a theoretical perspective, the lag length should be as many periods a change in the system will take to have an effect but not longer. Too many lags will lead to loss of degrees of freedom while too few lags will lead to omitted-variable bias. The most common rule of thumb is to use as many lags the number of periods the time series is divided into. That is, use for lags for quarterly data, 12 lags for monthly data and so on. This suggests that I should be using 12 lags. There are, however, tests that can be conducted to see how many lags are appropriate. As can be seen in Table 3, when using Akaike's information criterion (the most preferred test according to Brooks (2008)), the recommended lag length is 11. LR test also suggests 11 lags while SBIC (another well used test) suggest 1 lag, a quite odd result for monthly data. Since two widely used tests suggest 11 lags, which is approximately the same as suggested by the rule of thumb, I will stick to the rule of thumb and use 12 lags in my VAR.

Table 3: Tests for determining optimal lag length using varsoc in Stata. That is, the Akaike's Information Criterion (AIC) recommends 11 lags. I tried increasing the number of maxlags to see another number of lags would be recommended that was above 11, but 11 was recommended even when I used 50 as maxlag. The likelihood ratio test also recommend 11 lags, but as discussed is AIC preferred.

lag	LL [a]	LR[b]	df	p	AIC[c]	SBIC[d]
0	-1367.166				6.209367	6.227912
1	-1206.259	321.8129	4	2.13E-68	5.497774	5.553407*
2	-1196.028	20.46256	4	0.0004046	5.469514	5.562236
3	-1188.682	14.69214	4	0.0053842	5.454339	5.58415
4	-1180.52	16.32262	4	0.0026154	5.435467	5.602366
5	-1167.146	26.74854	4	0.0000223	5.392953	5.596942
6	-1156.822	20.64775	4	0.0003719	5.364273	5.605351
7	-1154.835	3.973956	4	0.4095421	5.373403	5.651569
8	-1152.521	4.629568	4	0.3274593	5.381045	5.696301
9	-1148.452	8.137017	4	0.0866861	5.380735	5.733079
10	-1142.318	12.26775	4	0.0154674	5.371057	5.76049
11	-1134.303	16.03046*	4	0.0029786	5.352848*	5.779369
12	-1130.809	6.988706	4	0.1364863	5.355141	5.818751

[a] Log likelihood

[b] Likelihood ratio

[c] Akaike's Information Criterion, calculated as $AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T}$, where the number of equations is denoted K, the number of observations T and the numbers of parameters t_p.

[d] Schwarz's Bayesian information criterion, calculated as $SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T}t_p$

Consequently, my bivariate VAR model with 12 lags can be written as

$$\begin{aligned} SweEPU_t = c_1 + a_{1,1}SweEPU_{t-1} + a_{1,2}Returns_{t-1} + \\ + a_{1,3}SweEPU_{t-2} + a_{1,4}Returns_{t-2} + ... + \\ + a_{1,22}SweEPU_{t-12} + a_{1,23}Returns_{t-12} + u_{1,t} \end{aligned} \tag{2}$$

$$\begin{aligned} Returns_t = c_2 + a_{2,1}SweEPU_{t-1} + a_{2,2}Returns_{t-1} + \\ + a_{2,3}SweEPU_{t-2} + a_{2,4}Returns_{t-2} + ... \\ + a_{2,22}SweEPU_{t-12} + a_{2,23}Returns_{t-12} + u_{2,t} \end{aligned} \tag{3}$$

5 Findings

The estimated coefficients for the VAR model specified in equations (2) and (3) can be seen in Table 4. The Granger causality test performed on my VAR can be seen in Table 5. The impulse response function graphs for the VAR estimation can be seen in Figure 7. The effect of in impulse from SweEPU on Returns negative (a one standard deviation increase from SweEPU decrease Returns with less than 1 percent) in the first period after the impulse and then not statistically significant. The effect of Returns on SweEPU is statistically significant for several periods after an impulse and the relationship is negative also here. One and two periods after the impulse, the one standard deviation increase of Returns decrease the Swedish EPU index by about 2. The effect then varies from not significant to mildly negative to not significant and so on.

In summary, the relationship between Returns and SweEPU is according to my findings negative. The effect of Returns on SweEPU is statistically significant for several periods after an impulse from Returns, but the effect of SweEPU on Returns in not statistically significant. This is also what my Granger causality Wald tests show. Returns Granger cause SweEPU, since we can reject the null

Table 4: Estimates from the VAR

VARIABLES	(1) SweEPU	(2) Returns
L.SweEPU	0.406***	-8.71e-05
	(0.0481)	(0.000207)
L2.SweEPU	0.0719	0.000128
	(0.0516)	(0.000222)
L3.SweEPU	-0.0252	0.000363
	(0.0515)	(0.000221)
L4.SweEPU	0.0384	0.000183
	(0.0516)	(0.000222)
L5.SweEPU	0.128**	-0.000164
	(0.0515)	(0.000221)
L6.SweEPU	0.132**	-2.92e-05
	(0.0516)	(0.000222)
L7.SweEPU	-0.0278	0.000263
	(0.0511)	(0.000220)
L8.SweEPU	-0.00242	-0.000200
	(0.0511)	(0.000220)
L9.SweEPU	0.0610	-0.000354
	(0.0513)	(0.000220)
L10.SweEPU	-0.0565	0.000128
	(0.0518)	(0.000223)
L11.SweEPU	0.155***	-0.000138
	(0.0521)	(0.000224)
L12.SweEPU	0.0629	0.000309
	(0.0476)	(0.000205)
L.Returns	-44.68***	0.141***
	(11.20)	(0.0482)
L2.Returns	5.130	-0.0314
	(11.45)	(0.0492)
L3.Returns	-18.51	0.104**
	(11.41)	(0.0490)
L4.Returns	-8.687	0.00136
	(11.47)	(0.0493)
L5.Returns	2.084	0.0336
	(11.47)	(0.0493)
L6.Returns	23.77**	0.0289
	(11.45)	(0.0492)
L7.Returns	12.71	-0.0490
	(11.49)	(0.0494)
L8.Returns	6.127	0.0189
	(11.49)	(0.0494)
L9.Returns	-15.18	-0.00641
	(11.47)	(0.0493)
L10.Returns	-38.17***	-0.0447
	(11.33)	(0.0487)
L11.Returns	-18.39	0.0306
	(11.47)	(0.0493)
L12.Returns	16.60	0.0131
	(11.29)	(0.0485)
Constant	6.795*	-0.0304*
	(3.987)	(0.0171)
Observations	441	441

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

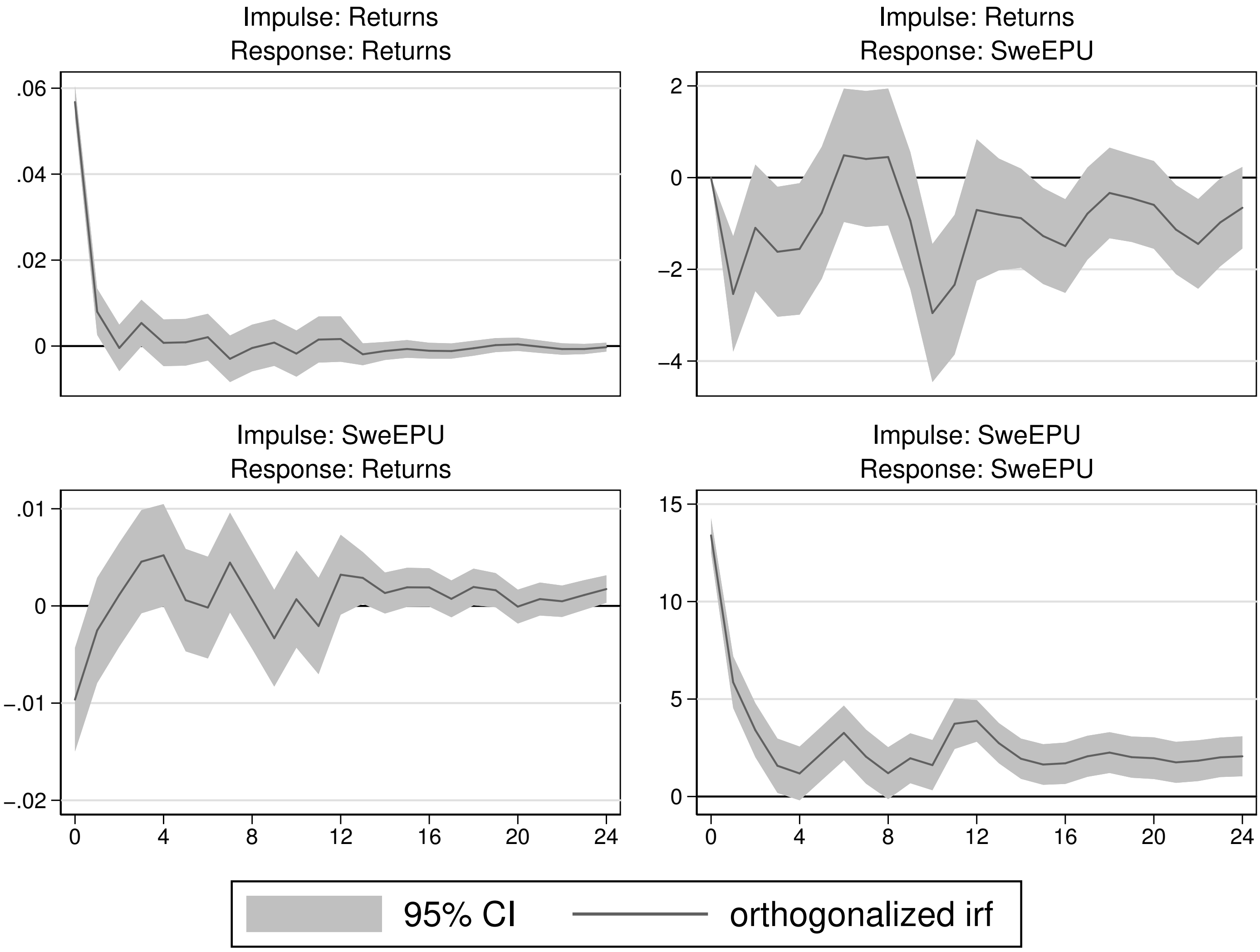

Figure 7: Impulse-response graphs for my estimated VAR. The graphs show the effect of a one standard deviation impulse from the impulse variable on the response variable. That is, the two top graphs show the effect of a one standard deviation impulse of Returns on Returns respectively SweEPU and the two bottom graphs show the effect of a one standard deviation impulse from SweEPU on Returns and SweEPU. The y-axis is shown in the unit the response variable was specified in the VAR and the x-axis shows the number of periods after the shock.

Table 5: Granger causality Wald tests performed on my VAR. The null hypothesis is that the excluded variable does not Granger cause the variable under "Equation".

Equation	Excluded	χ^2	df	$Prob > \chi^2$
SweEPU	Returns	43.053	12	0.000
Returns	SweEPU	17.776	12	0.123

hypothesis that lags of Returns do not Granger cause SweEPU at a 1 % level. We cannot, however, reject the null hypothesis that lags of SweEPU do not Granger cause Returns at any relevant level of significance (a p-value of 0.123).

As follows, the answer to my research question "Does domestic economic policy uncertainty affect stock market returns in Sweden?" seem to be "No". My findings points to the conclusion that the direction of causality is the opposite, stock returns in Sweden seem to affect SweEPU in the future, but we cannot say that SweEPU affects stock returns at any relevant level of significance.

6 Testing the validity of the results

Several postestimation tests have been performed on my estimated VAR model. I have tested if my model is stationary and if my model show autocorrelation and heteroskedasticity. I have also tested if my error terms are normally distributed, although they do not need to according to modern econometrics.

Regarding stationarity, I have look at the eigenvalue stability condition of my estimated VAR as shown in Table 6. The conclusion is that my model in stationary.

The presence of autocorrelation of the errors terms in an estimated time series model can harm the accurateness of the estimates and the inference. I have tested for this in my estimated VAR using a Lagrange-multiplier test. Autocorrelation is not a severe issue in my model, since I can accept the null hypothesis of no autocorrelation for all my lags at a 5 % level except for lag 12.

Using the White test[4] to test if my estimated VAR shows heteroskedastic error

[4]I use Orhan Karaca's Stata script to perform a White test in a VAR, which can be found here `https://sites.google.com/site/okaraccaeng/code`

Table 6: Postestimation test for my estimated VAR: Eigenvalue stability condition. My VAR satisfies the stability condition and thus is stationary, since all the eigenvalues are inside the unit circle.

Eigenvalue			Modulus
.9772894			.977289
.4630814	+	.7823358i	.909117
.4630814	-	.7823358i	.909117
.723127	+	.4883701i	.872593
.723127	-	.4883701i	.872593
-.4553222	+	.7386074i	.867675
-.4553222	-	.7386074i	.867675
-.02246941	+	.8571742i	.857469
-.02246941	-	.8571742i	.857469
-.5451399	+	.6586888i	.855014
-.5451399	-	.6586888i	.855014
.2999582	+	.7799624i	.835653
.2999582	-	.7799624i	.835653
-.7959011	+	.2440247i	.83247
-.7959011	-	.2440247i	.83247
.7379218	+	.3146962i	.802223
.7379218	-	.3146962i	.802223
.7693485			.769349
-.7677888			.767789
-.6874227	+	.3386012i	.76629
-.6874227	-	.3386012i	.76629
-.08533677	+	.722067i	.727092
-.08533677	-	.722067i	.727092
.3026362			.302636

Table 7: Lagrange-multiplier test. H0: no autocorrelation at lag order

lag	χ^2	df	$Prob > \chi^2$
1	5.3579	4	0.25250
2	6.8784	4	0.14245
3	2.9676	4	0.56325
4	4.8833	4	0.29948
5	1.0320	4	0.90490
6	3.6601	4	0.45396
7	3.5031	4	0.47740
8	3.6292	4	0.45851
9	1.6683	4	0.79647
10	6.0881	4	0.19267
11	4.6798	4	0.32176
12	12.2966	4	0.01528

terms, I got a χ^2 of 146.487 and a p-value of 0.427. Hence I cannot reject the null hypothesis of homoskedasticity. Consequetly, heteroskedasticity should not be a problem in my model.

According to my Jarque-Bera, Skewness and Kurtosis tests, the error terms in my VAR does not follow a normal distribution, as can be seen in Table 8. This, however, does not impose a severe problem due to my large sample size (N=453).

As discussed in section about specifying the model, the SBIC test for the number of lags that ought to be used suggested I use one lag. In order to check the robustness of my model with 12 lags further, I did try estimating my VAR with one lag. The result was that the IRF functions did not show a statistically significant effect of Returns on SweEPU and the effect of SweEPU on Returns is only significant in 1 period after the impulse, and the effect is very small. Furthermore, a model with one lag do not show any Granger causality at all regardless of direction (on a 5% level). Also, the estimated model show autocorrelation and heteroscedasticity. In summary, using only on lag instead of 12 gives a more poorly estimated model. Hence, the choice of using 12 lags seems to be accurate in order to estimate an appropriate model, and is also in line with theory.

Table 8: Jarque-Bera, Skeness and Kurtosis tests of my estimated VAR. The null hypothesis is that the errors terms are normally distributed, which I can reject in almost all tests.

	Jarque-Bera test			Skewness test				Kurtosis test			
Equation	χ^2	df	p	Skewness	χ^2	df	p	Kurtosis	χ^2	df	p
SweEPU	101.396	2	0.0000	.72962	39.127	1	0.0000	4.8409	62.269	1	0.0000
Returns	50.941	2	0.0000	-.03641	0.097	1	0.7549	4.6634	50.843	1	0.0000
ALL	152.337	4	0.0000		39.225	2	0.0000		113.112	2	0.0000

7 Discussion

The fact that there seems to be a relationship between stock returns in Sweden and Swedish economic policy uncertainty is not surprising for the reasons discussed in the introduction. What, perhaps, was more surprising was the direction of causality that my findings imply. Stock returns affect policy uncertainty and not the other way around. This does contradict Pástor and Veronesi's theoretical model, and it does not provide support for Wisniewski's "bi-directional feeback loop", but does not necessarily contradict the other empirical studies examining stock returns and EPU I brought up in the introduction. Antonakakis et al. do not talk about the direction of causality, neither do Sum's study.

The first caveat that needs to be said here is that Granger causation is not the same as causation in an ontological sense. In order to show a causal relationship in strict sense, one has turn to other econometric techniques such as using instruments. How to use exogenous instruments to prove causation in macroeconomics using VARs are discussed in for example Stock and Watson (2005).

Another possible flaw with my study that could be an explanation to the unforeseen causal direction could be my data. I could only access monthly data on the Swedish EPU index, and since stock data can be obtained daily and with even more intervals, more finely granulated data would be very interesting to study. Perhaps the effect would have turned out differently if I had used more finely granulated data (daily or even intradaily), since a lag of one month could be considered as a long period on the stock market and the news pace is fast. I have been in touch with one of the authors ofArmelius et al. who generated an experimental timeseries of 10 years of daily data on the Swedish EPU index, but unfortunately this data was not reliable enough since it differed substantially from the monthly published index. The data collection is time consuming, and thus I did not follow through on this path.

Another effect could also have shown potentially if I had included contemporaneous effects in my VAR. As mentioned in the introduction, this would prevent me from not making an a priori assumption about direction of causality. However, now that I have evidence that the direction appears to be from stock market returns to SweEPU, a future refinement of my model in future studies could be to make a structural VAR with contemporaneous effects. Perhaps the effect is stronger or weaker then.

Furthermore, including more variables in the VAR could be interesting and perhaps capture other effects. For example, including other variables that has been proven to have an impact on SweEPU could be interesting, to isolate the effect from stock market returns. A natural next step for further research would be to estimate a multivariate VAR with one or several of the variables Armelius et al. showed have a connection with EPU in Sweden, such as more macro related variables like GDP growth, household saving rate, investment, repo rate, unemployment. This could, on the contrary, lead to problems with multicollinearity due to the stock market being very closely linked to those macro variables.

The fact that the effect of stock returns on EPU in Sweden is not very strong is consistent with Wisniewski (2016)'s conclusion of policy uncertainty being more important for emerging economies and Pástor and Veronesi (2013)'s theoretical model claiming this. The negative relationship between stock returns and policy uncertainty is consistent with earlier research on the area, both empirical and theoretical papers as discussed in the introduction. My findings could help explain the results of Sum (2012a) who do not discuss the direction of causality in his paper showing that US EPU forecasts stock returns in the EU negatively. The Swedish case show in this paper may, however, not be generalizable to other European countries, something that would be interesting to study further.

In my study, I only look at Swedish data. A natural step for a small open economy like Sweden would be put this further into an international context. Since I have confirmed a relationship between SweEPU and the Swedish stock market and that earlier studies have confirmed the relationship between US EPU and the Swedish stock market, it could be of interest for future studies to compare the two. That is, to compare what affects the Swedish stock market the most, US or Swedish EPU. This has been studied for other variables. (Colombo, 2013), for example, show that US EPU affect industrial production and prices in the Euro area more than EU EPU does, and it would be interesting to see if this effects can be found for the stock market.

Furthermore, comparing different EPU indices from different countries and their effect on the stock market in Sweden could be of interest. As mentioned, US EPU and EU EPU are close to hand. Also EPU for Germany by itself would be interesting to include since Armelius et al. showed a relationship with German EPU. The case of Germany is interesting since the country have had very strong connections with Sweden historically regarding trade, cultural influence etc. The fact that Germany is Europe's strongest economy and most dominant player regarding international macroeconomics is in fact not captured by the European EPU index, since it is an un-weighted average of newspapers from France, Italy, UK, Spain and Germany. If looking at Germany's roll in the previous Greek crisis, one can expect that the uncertainty regarding economic policy from Germany specifically has a large impact of other countries.

The UK is another country who's economic policy uncertainty is included in the European index that could be interesting to study by itself, partly because London has been considered the financial capital of Europe but also in the context of Brexit. An interesting future study would be to compare an European index where UK is excluded (that is, a post-Brexit EU index) to the UK index and their respective connections to the Swedish stock market. Such study, however, ought to be conducted well after UK has legally left the EU and optimally a couple of years after in order to have enough post-Brexit observations.

Other than studying SweEPU in comparison with EPU from stronger economies than Sweden's, it would be compelling to compare the SweEPU with the global EPU index, which was created not long ago. However, the Swedish index is included in the global index, which could lead to econometric issues such as an over specification bias or collinearity. If looking away from the stronger economies, including EPU from Sweden's neighbour countries in the Nordics could give more answers. EPU indices for Finland, Denmark, Norway or Iceland has not been created yet, but given the popularity of the EPU index that many new country specific indices has been made recently, one can predict that such indices will be made soon.

Another type of further research that would be interesting would be to use other proxies than Swedish EPU to proxy for policy uncertainty. Though EPU is the most established index for uncertainty, the newspaper scraping might not capture all uncertainty or could perhaps capture other macrotrends than uncertainty. Hence it would be interesting to compare results from similar studies conducted with different proxies. For example could the alternatives to EPU that I wrote about in the introduction be interesting to study in a comparative study. Those have, however, not been made for Sweden, which makes construction of such indices necessary.

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