Political uncertainty intraday: how the stock market reacts

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ABSTRACT

Using the stochastic features of an asset pricing model based on consumption, this paper exploits the martingale properties of prices on short time-frames over the economic shocks, to measure the market response to political uncertainty using an index proposed based on political agents' movements tracked by news channels and modeled with VAR(p). The results contribute to the asset pricing literature showing that over a high-frequency environment, $S\&P$ 500's SPY index has a first response at one lag but also a significant response later, and its' reaction to political noise starts after one hour and takes as much as 6 hours and 30 minutes to settle, on 3 defined sprints with correction at the end of each, making up to a total of about 11% return.

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Political Risk, the risk related to politics and politicians' movements' direction and variability, is not well defined in the finance literature. Diamonte et al. (1996) uses the *International Country Risk Guide (ICRG)* as a measure, but Bekaert et al. (2016) states that sovereign spreads that are often used as information about political risk reflect many factors beyond political ones, so the usual proxy as a set of macro parameters can account for 17% to 31% of the variation in observed spreads for non-default periods. Baker et al. (2016) proposes a narrower scope by defining Economic Policy Uncertainty (EPU), aiming to just measure uncertainty over changes in policies that affect economy.

Instead of narrowing it down this paper takes a broader approach trying to measure Political Uncertainty as a whole, taking into account any movement in politics, to pin down if any disturbance in the current political status, can have an impact on the stock market. This is to allow dealing with lower frequency data, as the aim of this paper is to study the effects intraday, on short time-frames, of Political Uncertainty over the stock market.

According to Pástor and Veronesi (2013), although there are few modeling proposals for an asset price and political news relationship in finance literature, it is clear that political shocks, even though these are orthogonal to economic shocks, can have a negative impact, especially on weaker economies because it is a non-diversifiable risk associated with a set of political movement, thus the uncertainty towards these affect investors beliefs which in turn can depress asset pricing through the discount rate channel, but also pushing up volatility. Hence, there is a political risk premium, that is not idiosyncratic.

Cochrane (2005) relates the stochastic discount factor to the consumption growth model, showing that if the utility over consumption is constant but for some reason, there are movements in stock prices, and consequently returns, there must be a change to the discount factor to account for. The stochastic discount factor represents the risk aversion and its price in the theory.

Considering the discount rate for a consumption growth model, CAPM, or any other financial model, Cochrane (2011) shows that many times the price variation is due to discount-factor news and that considering cash-flow changes makes much more sense in a two-period model, but it is short-sighted to do it in a time-varying discount rates world, due to the constant changes of the factors that define the risk premia required by the market.

In a short time window, asset prices should behave as a martingale (e.g. Cochrane, 2005), since that there are no changes in demand or expectation differences in future returns. This paper exploits this result from finance theory, considering that prices varying in a small time-frame should have all the economic information precified, thus an effective control to test orthogonal information on this setting. As political uncertainty can be viewed as non-idiosyncratic to economic factors, a higher frequency measurent of any movement in the country's political status is proposed and afterwards a model is devised to test jointly if this aspect of uncertainty affects the stock market and if indeed, even with this orthogonal risk factor, asset pricing behaves as a random walk in this setting.

A weaker economy means the market responds more to political uncertainty than a healthier one, Kelly et al. (2016) when expanding the study over the option derivatives, shows that there is less chance of stability and the sole prospect of a political upset brings a higher risk premium. Political events seem to be closely related to variance and jumps in risk precification, and there is little evidence of political asymmetry affecting the market.

Pérez-Liñán (2007) explains a new political dynamic in Latin America, one in which there are no more coups, the change of power is dealt alongside the political system in vogue of each country, creating a clash between parties, branches which are mainly validated by media coverage, working as a peoples' representative and sometimes serving as the indicators of power shifting within politicians.

Then, Arbatli et al. (2017) while studying the impacts of political uncertainty over Japan concludes that although it is hard to pinpoint how the causality works, high policy uncertainty harms the macroeconomic performance and that past policy decisions and institutions shape the general response to uncertainty over new shocks.

The dynamics of political movements across media and people daily are tightly related to the future of a country. Acemoglu et al. (2018) shows that the daily variation in peoples' protests in Egypt can affect firms' valuation and therefore the stock market. This study also demonstrates how social media had some impact on protests, and even when those had no real effect on the political arrangement, it affected the prices of the firms that had tighter connections and dependence on the government.

Any significant change in the political uncertainty level thus affects the discount rate of the underlying pricing process and Lochstoer and Tetlock (2020) finds that market discount rate movement is the main determinant for market returns, accounting for as much as 74% variation.

The proposed index for the political uncertainty level is based on the Goldstein Scale (Goldstein, 1992) for each news released in the last 15 minutes, and with the market return in time t a VAR(p) is tested, evaluating the correlation between both intraday strucutres to see if it follows that both hypotheses that asset prices do not adhere to a random walk in a higher frequency setting and that political uncertainty affects, through the pattern laid by the measure, the stochastic discount factor changing prices even considering *ceteris paribus* for the economic factors.

The results show that in a tight time delta the return does not respond as a random walk, with a significant part of the market taking at least one hour to react to new economic information, and the proposed index (PUI) for measuring uncertainty shows a statistically significant relationship with the return promoting at some point as much as 0.12% response in the SPY return over a typical trading day of 6.5 hours.

I Literature Review

The consumption approach to finance theory is used to explain the core reasoning behind the methodology. The expected consumption over any period in the future, given a constant discount rate, is how assets are priced in equilibrium on a market without arbitrage that respects the one-price law. For a very short time delta, it is expected no significant changes in inter-temporal consumption but also a constant stochastic discount factor assumption is acceptable. Using this property of short time-frames as a control for idiosyncratic economic factors, but not political uncertainty, which can be more dynamic as expectations and directions can change with every news, especially with one that signals big movements or trouble.

A Defining Uncertainty

Bekaert et al. (2016) defines Political Risk as actions by political agents that lead to negative cash flows and so an agent can apply this risk discount and the rate representing systematic risk together. He discusses the availability of political risk ratings, which are mostly subjective, and that it is hard to quantify them, rendering the agent hostage to a subjective discount rate as an approximation.

Considering a space of possible actions in a politics set, it is clear that measuring all of it is out of reach without extensive research, hence Baker et al. (2016)'s choice of only measuring EPU, a smaller scope but the most tied to any economy, is an advance on the subject making it easier to measure, compare and even predict. It makes clear that some aspect of actions taken by politicians, and the uncertainty around it, harms the market.

On top of the EPU, Pástor and Veronesi (2013) studies its relationship with the market risk premia, finding that although this aspect of political uncertainty is orthogonal to economic risks, it influences agents' beliefs over possible costs of new policies creating a premium despite being unrelated to economic shocks. The results indicate that even a positive policy proposal, if high in its uncertainty, has an impact that can be negative and that in weaker economical cycles the impact of this uncertainty is higher. Arbatli et al. (2017) finds that in Japan, the uncertainty over economic policies also has negative impacts on macroeconomic performance, but it is hard to establish causal effects.

Instead of identifying all actions over a period or proposing measuring a subset, just finding how disturbances in its center of gravity affect asset pricing, thus the question is how any disturbance in agents' political beliefs affects asset pricing.

Pérez-Liñán (2007) analyses the recent development of the political dynamics in Latin America, stating that coups and riots are not a strategy considered in any power struggle in stable democracies, but clashes within the political realm are used to gauge public support and opposition power. Also, that an important political agent surged in influence recently, the media, as they ultimately decide whom to support, where to focus the stories, and how the people get information. Uncertainty is then taken from a news data stream, provided by the GDELT Project.

B Asset Pricing on Short Time-Frame

According to Hall (1978), in a constant interest rate model, the expected consumption's marginal utility on $t+1$ is only based on the marginal utility on t, and all other information is irrelevant. That implies the marginal utility, apart from a trend, is a random walk, a stronger stochastically implication is that only the previous lag on the time series is significant with a coefficient different than zero, and is impossible to improve the future marginal utility consumptions' forecast beside the taking the current level and considering the trend.

Hansen and Richard (1987) discusses the equilibrium of the market with no-arbitrage, on which current prices simply result from a function that represents uncertainty on the current prices, those can be understood as representations of non-negative pay-offs. Then, considering that any asset can be priced in or outside the mean-variance frontier, thus any return can be expressed as:

$$R^i = R^* + w^i R^{e*} + n^i, \quad where\ E(n^i) = 0, \tag{1}$$

where w^i is a number, R^* the return corresponding prices, R^{e*} returns with price zero, and n an excess return, being all three orthogonal.

If the return affects prices, than it either affects $u'(c_{t+1})$ or the inter-temporal preferences through the *SDF*. As on the short window proposed the marginal utility should be constant, then any changes should be captured by the discount rate channel. Cochrane (2011) shows how a lot of variation in prices comes from discount-factor news, and in a time-varying world, it is unrealistic to take it as constant. Recessions are usually more linked to the changes in risk instead of the desire to change future consumption.

Thus, the discount-rate channel should be the only one to move with preferences in such a situation, with the theory indicating that any change in equilibrium prices, in a no-arbitrage situation, is dealt with through a varying *SDF*, on equation 3 the β that should be constant, if and only if it represented only the risk premium from economic factors, but if the policy uncertainty affects prices, beliefs, and inter-temporal preferences, then β captures all the effects of the *PUI*.

C Political Shocks and Market

Diamonte et al. (1996) discusses how political risk relates to stock returns, using an index based on specialists' opinions, suggesting that changes in risk levels have a bigger effect on emerging markets, but at the time the results suggested a convergence of different markets, indicating that the difference between countries might narrow down.

The fact that political factors are orthogonal to economic ones, does not render them in the space of excess returns, where their price equals zero. Pástor and Veronesi (2013) observes that political uncertainty impacts through changing the risk premium by its component that can be viewed aside as a political risk premium, which is state-dependent and has bigger effects on weaker economies. On those weaker conditions, political risk tends to make a bigger part of the total risk premium. Besides the price, political shocks also affect volatilities and correlations of stock returns.

Baker et al. (2014) shows that as the U.S.A. government grows, also the polarization in politics grows, this rhetorical battle over political power affects how economic policies are done and promotes a swing probability with every election, raising the stakes in presidential elections.

Over Japan, Arbatli et al. (2017) through a VAR model shows that uncertainty around policies, when rising, foreshadows a deterioration in the country's macroeconomic performance, being felt in investment, employment and output. Global measurement of uncertainty also impacts in the same direction, showing that it has significant forward-looking information for the market.

Kelly et al. (2016) exploits major political events to make sure the uncertainty proxy used is not reflecting any macroeconomic fundamental, showing that implied volatilities are especially high before key events, and shows that political uncertainty has a definitive effect on the state price density, with a risk premium attached to it. In theory, the news flow gives signals to agents about political events and their political costs.

When the politicians have much power over firms, Acemoglu et al. (2018) finds that in Egypt, throughout the Arab Spring, protests triggered uncertainty around the political group in power, which then affected all the stocks related to them, even without a *de facto* change in power. Indicating that this uncertainty affected these firms' rents valuation for the market agents.

In an ample perspective, Brogaard et al. (2020) uses U.S.A. political uncertainty around elections as a proxy for global uncertainty, suggesting that there is a spillover effect of a change in the global risk aversion, through the discount-rate channel, and the effects are not contained on domestic borders.

II The Model

The nature of asset price levels and the expected growth of political uncertainty requires a model able to deal with those integrated processes, hence a Vector Autoregressive Model (VAR) is proposed on prices at 15-minute intervals taken from publicly available data.

A The Random Walk of Prices

Hall (1978) discusses how a stochastic view over the Life Cycle-Permanent theory shows that only a one lagged period of consumption should have a coefficient different than zero, meaning that marginal utility obeys a random walk, implying that consumption is unrelated to any economic variable observable in earlier periods, in short:

$$E_t[u'(c_{t+1})] = \beta u'(c_{t+1}) + \varepsilon_{t+1} \quad where \quad E_t(\varepsilon_{t+1}) = 0. \tag{2}$$

Taking the general form of asset pricing, the basic condition can be written as:

$$p_t u'(c_t) = E_t[\beta u'(c_{t+1})(p_{t+1} + d_{t+1})]. \tag{3}$$

Being β the stochastic discount factor (henceforth, *SDF*), which represents the discount over inter-temporal preferences in consumption (or the discount rate channel on cash flow models), it can be expressed, as Cochrane (2005) demonstrates as:

$$\frac{u'(c_{t+1})}{u'(c_t)} = \frac{1}{\beta R^f} + \varepsilon_{t+1}. \tag{4}$$

Although the risk-free rate (R^f) is not constant, in a very small time frame, such as a 15-minute gap, it is relatively constant, and the SDF also can be considered close to 1, as the SDF expresses the discount/premia required for a state of the economy, which isn't expected to change in this short window. Meaning that in general, if $\text{var}_t^2(\varepsilon_{t+1})$ is constant, the pricing process, as a time series is a random walk:

$$p_{t+1} = p_t + u_{t+1}. \tag{5}$$

Or in terms of return, which can be defined as $\Delta p_{t+1} + 1$ which in this case also equals p_{t+1}/p_t because essentially, without any changes in the economy $E(p_{t+1}) = E(p_t)$, the martingale can be described:

$$\frac{p_{t+1}}{p_t} = 1 + \varepsilon_{t+1}. \tag{6}$$

B Political Uncertainty Index

Pérez-Liñán (2007) proposes a new political dynamic, over which media coverage presents as a big player and often gives weight to public outcry. Baker et al. (2016) creates a measurement of policy uncertainty over newspaper analysis, generating an index able to capture the level of economic risk related to changes in policies, demonstrating the long-lasting impulse response to politicians' signals. Acemoglu et al. (2018) uses the news to track protests in Egypt and relates the impact of political uncertainty on different parties' domination over companies that are tied to them in some way. This study screens the GDELT database for news on the topic.

Using the Goldstein Scale (GS) from Goldstein (1992) for each data point on GDELT Event Database, an index is created on the political situation on media of each 15-minute interval, by averaging the GS over several articles by time-frame. Although there should be a high variance between each time-spot on some news and the distribution between the positive and negative articles, all points are treated with the same weight to summarize the difference between periods, not intra.

Baker et al. (2014) and Arbatli et al. (2017) find that uncertainty around politicians' choices has a significant relationship with stock markets. Kelly et al. (2016) states that although political uncertainty is, in theory, orthogonal to economic factors, it has statistical evidence that it impacts option prices. Dugast (2018) shows that if the market is in equilibrium, unexpected news triggers trading volume and generates a change in prices.

The Political Uncertainty Index, over a fifteen-minute time frame, is proposed as scaling the GS average level and then generating a natural log difference from the average level calculated for the whole previous window to capture the change over the last *political state*. Although in theory (Hall, 1978, e.g.) all information should be available in the last price, following Acemoglu et al. (2018) there is statistical evidence that only the last day of news has relevance, uncertainty is measured over a state, which is then compared to the mean tone on a window, tested up to a day worth of data.

Scaling the $mean(GS)_t$, where t is the *date time*:

$$GSscaled_t = \frac{mean(GS)_t + 11}{10}, \tag{7}$$

and calculating the average political tone for the time t over the last window of size w:

$$Political\ State_{t,w} = \frac{\sum_{n=1}^{w} GSscaled_{t-w+n}}{w}. \tag{8}$$

The Political Uncertainty Index (PUI) is therefore defined by:

$$PUI_{t,w} = ln\left(\frac{GSscaled_t}{Political\ State_{t,w}}\right) = ln(GSscaled_t) - ln(Political\ State_{t,w}) \tag{9}$$

C Vector Autorregressive Model

Hansen and Richard (1987) discusses how pricing is related to changes in other dimensions, so a dynamic model of asset pricing should specify the changing information available to economic agents, and its decomposition or projection over prices, is how it affects the risk premia of today. By choosing a small time frame, there should be no change in information available over economic factors, so a random walk(5) is expected over this dimension.

Per Pástor and Veronesi (2013), political uncertainty although orthogonal, affects prices through the stochastic discount factor, thus considering these two dimensions the final model, that all the economic movement is already priced on p_{t-1}, and that no change on marginal consumption level is expected is:

$$\frac{p_{t+1}}{p_t} - 1 = +\gamma PUI_t + \varepsilon_{t+1}. \tag{10}$$

But according to findings from Kelly et al. (2016), the state of the economy, information already priced in our model by p_{t-1}, affects the risk premium for political uncertainty, thus the PUI can be estimated as:

$$PUI_{t+1} = PUI_t + \beta p_t + \varepsilon_{t+1}. \tag{11}$$

This equation is only true if the economic state of a country has all the information necessary to explain the political uncertainty change over an expected base level of uncertainty. This assumption is taken as true for the model, thus all agents have complete information and the equilibrium price describes the aggregation of the market, as suggested by Hansen and Richard (1987).

The proposed model, considering the properties of the measured return and PUI which is calculated also as a difference of a current value to a moving average, can be described as a VAR model, as described:

$$\boldsymbol{AX} = \boldsymbol{B_0} + \sum_{i=1}^{p} \boldsymbol{B}_i \boldsymbol{X}_{t-i} + \boldsymbol{B}\varepsilon_t, \tag{12}$$

and since previous studies show that political uncertainty affects the return, the Cholesky identification is proposed with,

$$\boldsymbol{A} = \begin{bmatrix} 1 & 0 \\ a_{21} & 1 \end{bmatrix}, \quad \boldsymbol{X} = \begin{bmatrix} pui_t \\ return_t \end{bmatrix}. \tag{13}$$

III Data

To gauge the market price, S&P 500 index prices are used at the closure of each 15-minute tick, since this is also the time frame available from the GDELT Project. The index prices for S&P 500 and Chicago Board Options Exchange's CBOE Volatility Index (SPY, VIX respectively) is provided by the Alpha Vantage API and range from *2020-06-03 09:30:00* to *2021-12-31 16:00:00*, as regular trading hours go from 9:30$a.m.$ to 4:00$p.m.$

Since the market hours are limited when running the model with the PUI being calculated non-stop and daily, it is important to decide what happens to the observations outside the open market. For this approach, all PUI generated at closed hours are discarded, Hall (1978) and Hansen and Richard (1987) demonstrate how prices have all information at equilibrium, and PUI is just a price difference between last data point and the window preceding it, so it already gauges all the instantaneous market uncertainty at that time.

Market makers are not required to participate in and outside market hours, which typically spans 26 periods of 15 minutes per trading day, but after-market adds as many as 36 slots with potentially different dynamics in the U.S.A. stock market, thus this study opts to focus on normal trading hours because it is the time where all investors can effectively influence prices.

A Measuring Uncertainty from News

The Political Uncertainty Index is calculated using the whole GDELT Database with updates in 15 minutes periods. Goldstein (1992) proposed a classification of events to enable statistical studies, especially time-series models, hence called Goldstein Scale (GS). Offering a range of values gauged by specialists from -10 indicating a military attack, the apex of instability, and military aid at $+8.3$, the highest grade government help provided, with a overextended economic aid, with a weight of 7.4 on the GS.

The choice of the GDELT Project, reflects the extensive data points that the database provides, even though there are shortcomings, such as the lack of repetition filtering discussed by Ward et al. (2013) who also compares it to a similar project funded by the United States Defence Advanced Research Projects Agency($DARPA$) showing that similar results can be achieved on this open source project. The GDELT database provides a Goldstein Scale to each news data point.

The Political Uncertainty Index expresses the change in the political *status quo* on short windows and is calculated as described in (9), a scaled log-difference over the moving average of the last window. This rolling window is not previously defined or suggested in the literature, so the study tests for various windows ranging from 2 (a 30-minute interval) to 40 ticks (more than a typical trading day).

When parsing all the articles from GDELT Event Database for this study more than 100 million articles were accounted for and their GS values were averaged for each tick to build the index.

IV Results

Since the best window over with the PUI (9) is calculated is unknown, a range of the time-frames is tested, basically measuring the current tone over a recent state in time as described in the table below,

Table I: Ranges of PUI

Window	**2**	**4**	**6**	**8**	**10**	**12**	**14**
Time frame	30min	1hr	1.5hr	2hr	2.5hr	3hr	3.5hr
Window	**15**	**16**	**18**	**20**	**25**	**30**	**40**
Time Frame	3.75hr	4hr	4.5hr	5hr	6.25hr	7.5hr	10hr

As the normal trading hours spans 6.5 hours on a normal trading day, and because the price information should propagate fast in a market, larger windows are not the goal of this research.

A Descriptive statistics

Considering the rolling window usage to calculate PUI, more preceding data from the GDELT project is used to avoid different data sizes for each specification. As the statistics are very similar, the 4-hour window will be used as it is the specification with the highest p-value on the whiteness test (15.7%). The *Return* is calculated over the SPY index and VIX is the rolling percentage change (1 step) for the volatility index.

Table II: Variables statistics

	PUI	**Return**	**Vix**	**Close**
Count	10603	10603	10603	10603
Mean	−0.00161	−0.00051	0.00655	388.99
Std. Dev.	0.04033	0.14638	0.70998	51.21
Min.	−0.18013	−1.01569	−7.11009	289.45
25%	−0.02695	−0.06923	−0.30328	340.49
50%	−0.00000	−0.00637	0.02939	388.31
75%	0.02526	0.06147	0.34710	434.42
Max.	0.19003	1.46277	5.32019	477.33

It is interesting to note from table II that in general, the PUI measure usually shows few changes in tone from one period to the last considered window (henceforth called *state*), but it has some spikes indicating that at some periods, the change in tone is expressive in the 15-minute window, the VIX linear correlation to $Return$ is high, as expected. For a 4-hour state, PUI's max value is almost 5 times the standard deviation from the mean.

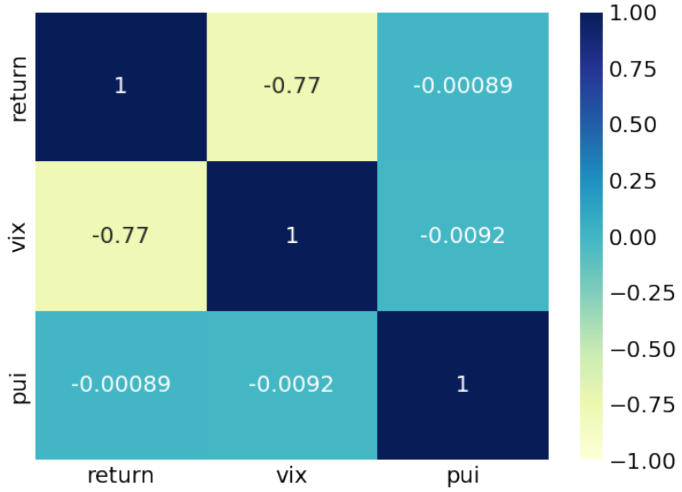

Figure 1: Correlation Map

The correlation heatmap (1) shows a low correlation between the uncertainty index and both VIX and $Return$, indicating that if it brings any information that predicts the $Return$, it indeed expresses another dimension related to SPY price and the VIX linear correlation to $Return$ is high as expected. Figure 2 presents the time series for both used measures in the VAR model.

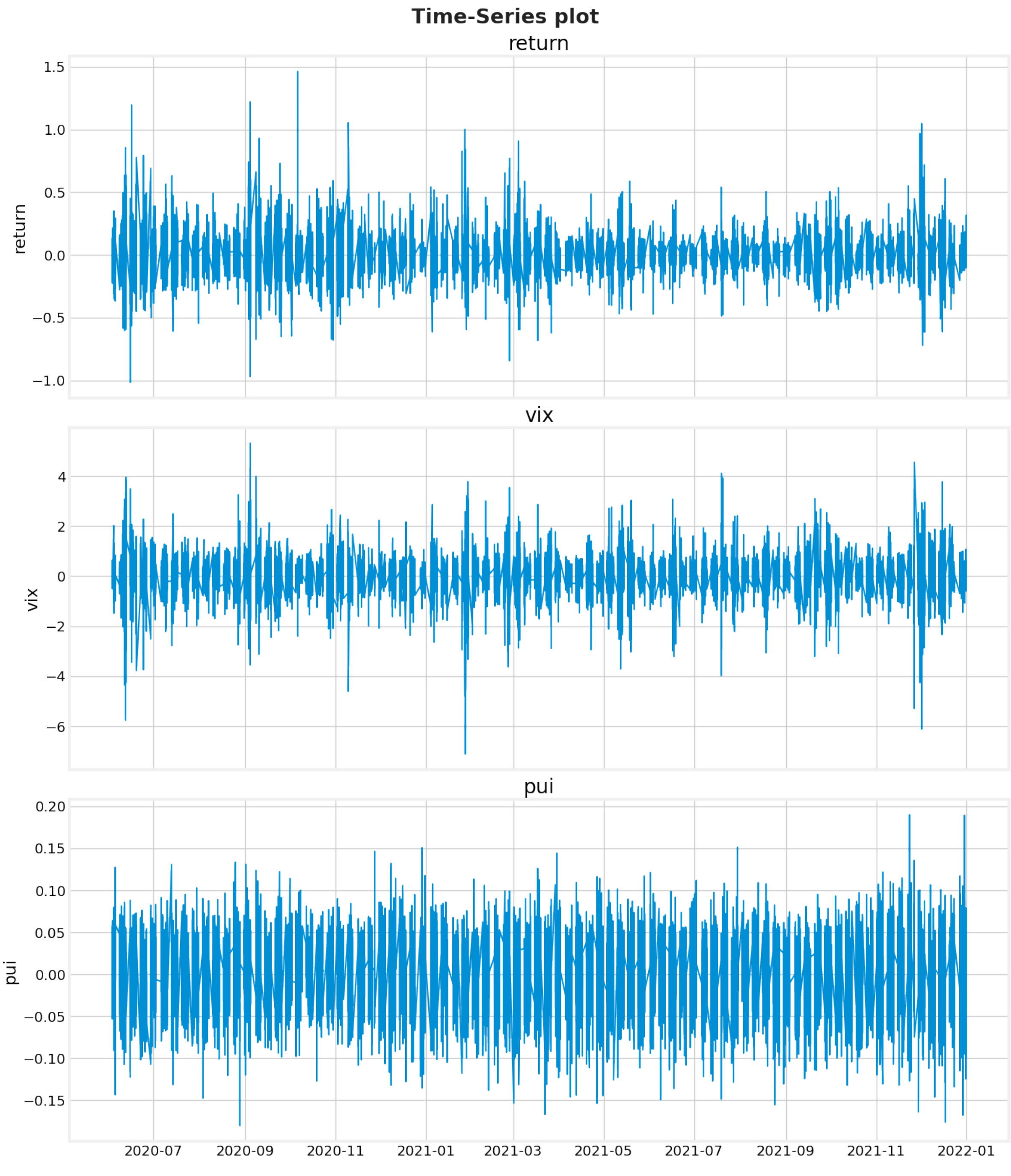

Figure 2: PUI, VIX and Return time series

Although all series seem stationary, it is not obvious that there is no process such as a moving average or even an autoregressive relationship. Figures 3,4 and 5 shows the autocorrelation and partial autocorrelation (provided by the *yule-walker method*) for PUI and return respectively for up to 40 periods, more than a trading day (27 periods). PUI displays some structure between 6 to 17 periods, an the return has an AR(1) indication but also some significant lags at 4,5,11 and 12 periods.

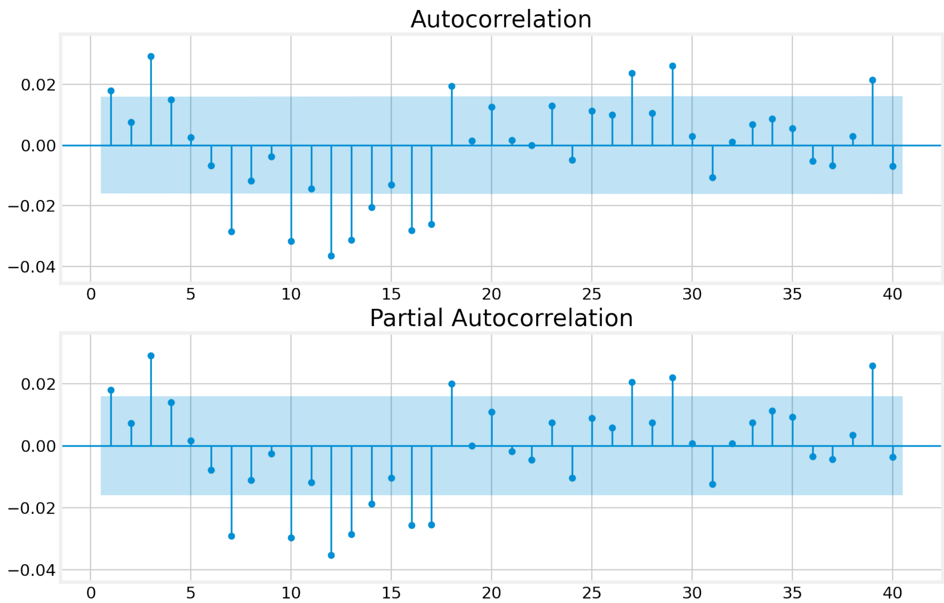

Figure 3: PUI *acf* and *pacf*.

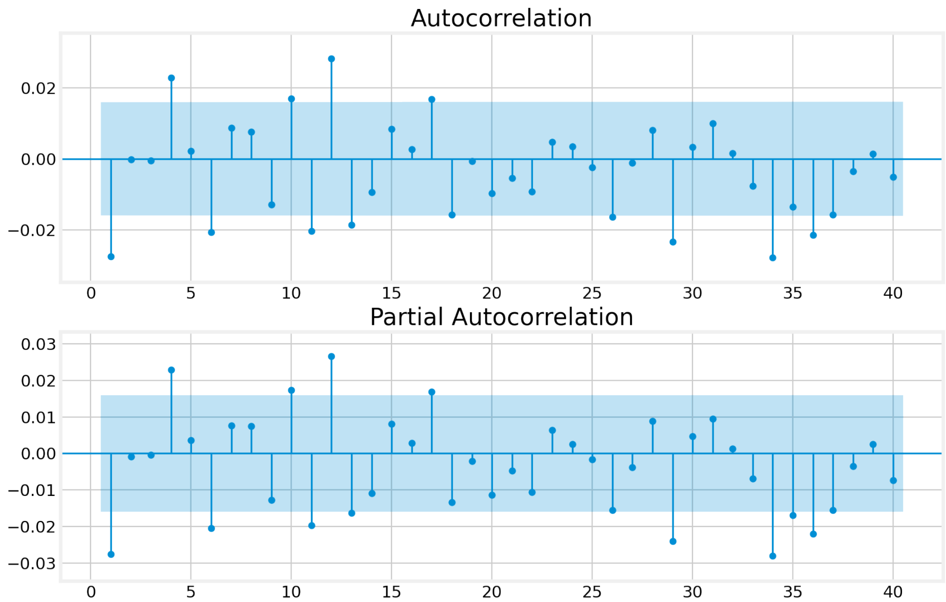

Figure 4: Return *acf* and *pacf*.

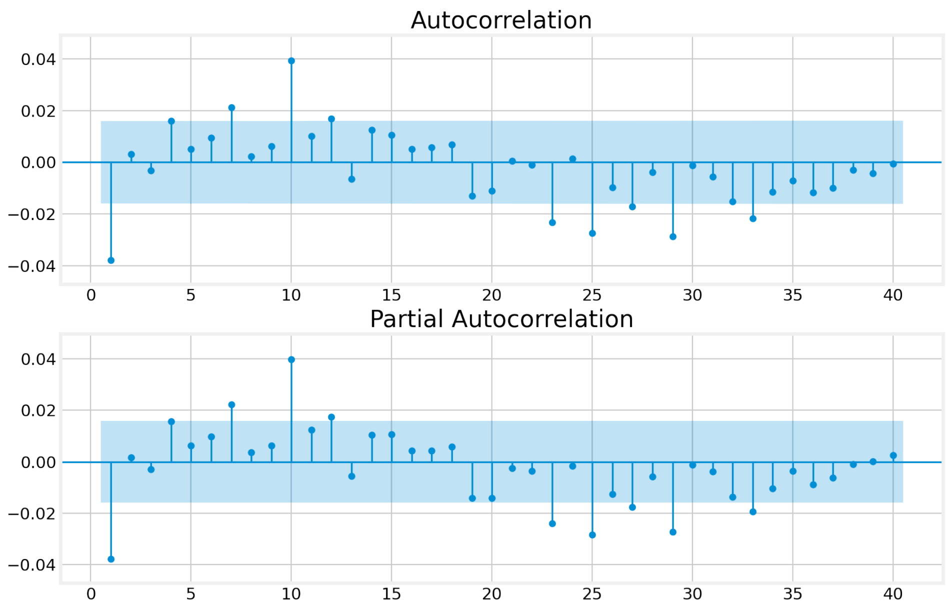

Figure 5: VIX *acf* and *pacf*.

B *Unit-root tests*

From the figures (3,4), it is clear that there is some data generating process for both series, before following with the VAR estimation, *ADF* and *KPSS* are used to make sure none of the variables presents unit-root. The results are presented on tables III and IV, with the ADF lag being selected with the *AIC* criterion and the KPSS lag being defined as per Franses and Hobijn (1998).

Table III: ADF Statistics

		Return		
	constant	**c./trend**	**c./trend^2**	**none**
Statistic	-28.48	-28.49	-28.49	-28.48
p-value	0.00	0.00	0.00	0
lags	12	12	12	12
		PUI		
	constant	**c./trend**	**c./trend^2**	**none**
Statistic	-27.36	-27.75	-27.77	-26.92
p-value	0.00	0.00	0.00	0
lags	17	17	17	17

Table IV: KPSS Statistics

	Return	
	constant	**constant/trend**
Statistic	0.0604	0.0253
p-value	> 0.1	> 0.1
lags	1	1
Crit. at 1%	0.739	0.216
	PUI	
	constant	**constant/trend**
Statistic	1.5130	0.0432
p-value	> 0.1	> 0.1
lags	7	7
Crit. at 1%	0.739	0.216

The definition of the null-hypothesis of the ADF test is that there is unit-root and the KPSS the null hypothesis indicates no unit-root, and from both tables presented in 3 and 4 the conclusion is that both variables do not present a unit-root.

C VAR results

The VAR model specified in 12, is estimated on a range of states for PUI (11) as described on table I. Each specification was also run with a lag-order choice based on each criterion (*AIC*,*HQIC*,*SIC*) and table V presents the lag-order selected by *AIC* followed by a whiteness test (Ljung-box) to confirm if after lag selection there is still any process over residuals.

Table V: VAR lag-order by criteria

	AIC lag-order	
Window	**Lags**	**Ljung-Box**
2	14	164.1**
4	17	180.7*
6	17	208.4
8	17	242.6
10	17	277.9
12	17	310.4
14	17	344.5
15	17	358.7
16	17	374.5
18	17	437.0**
20	17	488.2***
25	17	609.9***
30	17	731.8***
40	17	935.4***

* is rejected at 10%, ** at 5% and *** at 1%

Due to the parsimoniousness of the *SIC* and *HQIC*, all of the estimations had only zero lags, and the lag order selected by those criteria didn't result in white noise residuals. The lag choice for testing over each window considered the rule $40+(window \times 2)$, meaning on a 16-period sized window the test was done considering up to 72 lags.

Kilian and Lütkepohl (2017) discusses the drawbacks of accepting the lag-order chosen by parsimonious criteria stating that even the AIC can be overly parsimonious in some cases, and since dealing with high-frequency data, it is counter-intuitive that the whole market would perfectly react within just a 15-minute gap, thus only the AIC results are presented here since it provides positive lag-order and residuals that pass the Ljung-Box test.

As not all models pass the whiteness test, only those without a null-hypothesis rejection of up to 10% are shown, and results are sorted by smaller to bigger PUI window size.

Table VI: VAR Results for windows 4 and 6

	1.00hr (4)		**1.50hr (6)**	
Lag	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$
constant	-0.004008^{***}	-0.000115	-0.003932^{***}	-0.000047
L1.*PUI*	-0.112999^{***}	0.018180	-0.052577^{***}	0.014849
L1.*return*	-0.003547	-0.026013^{***}	-0.003243	-0.026006^{***}
L2.*PUI*	-0.157720^{***}	0.007197	-0.075042^{***}	0.003373
L2.*return*	-0.002565	-0.000327	-0.002751	-0.000329
L3.*PUI*	-0.172770^{***}	-0.010395	-0.066864^{***}	-0.017896
L3.*return*	-0.003305	0.000217	-0.003966	0.000090
L4.*PUI*	-0.227078^{***}	0.057664	-0.090512^{***}	0.061483^{*}
L4.*return*	0.000407	0.023831^{**}	0.000530	0.023538^{**}
L5.*PUI*	-0.082166^{***}	-0.020364	-0.114470^{***}	-0.020904
L5.*return*	-0.001580	0.001916	-0.001924	0.001981
L6.*PUI*	-0.093043^{***}	-0.027844	-0.141158^{***}	-0.030529
L6.*return*	-0.001007	-0.019194^{**}	-0.001925	-0.019087^{**}
L7.*PUI*	-0.105441^{***}	-0.053689	-0.056090^{***}	-0.051600
L7.*return*	0.001999	0.008458	0.002025	0.008366
L8.*PUI*	-0.078960^{***}	0.013621	-0.043656^{***}	0.020267
L8.*return*	0.000679	0.005371	0.000668	0.005386
L9.*PUI*	-0.043833^{***}	0.056804	-0.034196^{***}	0.070662^{**}
L9.*return*	-0.000238	-0.012567	-0.001217	-0.012487
L10.*PUI*	-0.063671^{***}	0.007703	-0.057296^{***}	0.020691
L10.*return*	0.003918	0.017034^{*}	0.003599	0.017242
L11.*PUI*	-0.041317^{***}	0.038341	-0.036159^{***}	0.035977
L11.*return*	0.004024	-0.018590^{**}	0.004071	-0.018411^{**}
L12.*PUI*	-0.051264^{***}	0.033969	-0.050091^{***}	0.017840
L12.*return*	-0.000521	0.026597^{***}	-0.000704	0.026432^{***}
L13.*PUI*	-0.032135^{***}	0.049529	-0.026477^{***}	0.037049
L13.*return*	-0.002166	-0.017030^{*}	-0.001904	-0.017031^{*}
L14.*PUI*	-0.025057^{**}	0.049454	-0.015137	0.049121
L14.*return*	-0.000456	-0.010232	-0.000480	-0.010024
L15.*PUI*	-0.008591	-0.042266	-0.005504	-0.042071
L15.*return*	-0.003945	0.008392	-0.004295	0.008409
L16.*PUI*	-0.021598^{**}	-0.049475	-0.018227^{*}	-0.045545
L16.*return*	-0.000809	0.003340	-0.001167	0.003312
L17.*PUI*	-0.036407^{***}	0.080009^{**}	-0.038032^{***}	0.084469^{**}
L17.*return*	-0.003775	0.017138^{*}	-0.003906	0.017157^{*}

* is significant at 10%, ** at 5% and *** at 1%

Table VII: VAR Results for windows 8 and 10

	2.00hr (8)		**2.50hr (10)**	
Lag	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$
constant	-0.003597^{***}	-0.000053	-0.003252^{***}	-0.000105
L1.PUI	-0.027435^{***}	0.007668	-0.011435	0.011454
L1.*return*	-0.003700	-0.026054^{***}	-0.004051	-0.026099^{***}
L2.PUI	-0.039139^{***}	0.007823	-0.021377^{**}	0.005400
L2.*return*	-0.003154	-0.000307	-0.003646	-0.000411
L3.PUI	-0.023462^{**}	-0.012216	-0.002999	-0.008827
L3.*return*	-0.003756	0.000159	-0.004196	0.000181
L4.PUI	-0.039695^{***}	0.060100^{*}	-0.015698	0.063669^{*}
L4.*return*	0.000588	0.023516^{**}	0.000235	0.023688^{**}
L5.PUI	-0.056032^{***}	-0.023602	-0.028372^{***}	-0.028903
L5.*return*	-0.001688	0.001940	-0.001543	0.002029
L6.PUI	-0.072775^{***}	-0.032614	-0.041474^{***}	-0.032695
L6.*return*	-0.001867	-0.019215^{**}	-0.001977	-0.019086^{**}
L7.PUI	-0.101742^{***}	-0.054637	-0.065325^{***}	-0.056064
L7.*return*	0.001284	0.008479	0.001501	0.008418
L8.PUI	-0.095845^{***}	0.025685	-0.054929^{***}	0.023358
L8.*return*	-0.000217	0.005585	-0.000076	0.005402
L9.PUI	-0.006103	0.072904^{**}	-0.047208^{***}	0.074842^{**}
L9.*return*	-0.001174	-0.012612	-0.001837	-0.012544
L10.PUI	-0.031596^{***}	0.016975	-0.075370^{***}	0.012647
L10.*return*	0.003437	0.017193^{*}	0.002626	0.017257^{*}
L11.PUI	-0.014135	0.039575	0.000601	0.046738
L11.*return*	0.003762	-0.018315^{*}	0.003527	-0.018425^{*}
L12.PUI	-0.038565^{***}	0.020212	-0.022247^{**}	0.023416
L12.*return*	-0.000353	0.026561^{***}	-0.000681	0.026616^{***}
L13.PUI	-0.030051^{***}	0.038316	-0.017013^{*}	0.039305
L13.*return*	-0.001761	-0.017005^{*}	-0.002051	-0.016909^{*}
L14.PUI	-0.019137^{**}	0.040845	-0.007597	0.034789
L14.*return*	-0.000587	-0.010197	-0.000440	-0.010120
L15.PUI	-0.007080	-0.054983	0.000735	-0.064441^{*}
L15.*return*	-0.003969	0.008367	-0.003955	0.008441
L16.PUI	-0.013387	-0.048375	-0.016230^{*}	-0.055739
L16.*return*	-0.001052	0.003479	-0.001496	0.003359
L17.PUI	-0.029993^{***}	0.087341^{**}	-0.038337^{***}	0.075935^{**}
L17.*return*	-0.004312	0.017259^{*}	-0.004202	0.017183^{*}

* is significant at 10%, ** at 5% and *** at 1%

Table VIII: VAR Results for windows 12 and 14

	3.00hr (12)		**3.50hr (14)**	
Lag	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$
constant	−0.002397***	−0.000168	−0.002855***	−0.000127
L1.*PUI*	0.006914	0.007832	−0.001376	0.010131
L1.*return*	−0.003833	−0.026156***	−0.003779	−0.026166***
L2.*PUI*	−0.002796	0.011942	−0.009125	0.007585
L2.*return*	−0.002764	−0.000410	−0.002774	−0.000362
L3.*PUI*	0.018490**	−0.010161	0.010652	−0.009256
L3.*return*	−0.003387	0.000266	−0.003986	0.000267
L4.*PUI*	0.006155	0.065675**	−0.001810	0.066423*
L4.*return*	0.000781	0.023777**	−0.000021	0.023712**
L5.*PUI*	−0.004874	−0.033311	−0.014131	−0.031232
L5.*return*	−0.001508	0.002037	−0.001834	0.001956
L6.*PUI*	−0.014240	−0.038140	−0.025355*	−0.035387
L6.*return*	−0.002422	−0.019211**	−0.002367	−0.019131**
L7.*PUI*	−0.035980***	−0.048175	−0.045822***	−0.053615
L7.*return*	0.001353	0.008312	0.001550	0.008439
L8.*PUI*	−0.019949**	0.028605	−0.031642***	0.023479
L8.*return*	−0.000511	0.005432	−0.000214	0.005468
L9.*PUI*	−0.011204	0.079943**	−0.024239**	0.080344**
L9.*return*	−0.001591	−0.012540	−0.001587	−0.012557
L10.*PUI*	−0.036345***	0.013210	−0.050769***	0.015658
L10.*return*	0.002842	0.017204*	0.002852	0.017133*
L11.*PUI*	−0.017621*	0.045941	−0.035307***	0.045709
L11.*return*	0.003408	−0.018351*	0.003196	−0.018365*
L12.*PUI*	−0.042433***	0.023063	−0.057168***	0.020845
L12.*return*	−0.000999	0.026693***	−0.001207	0.026768***
L13.*PUI*	−0.035671***	0.033020	−0.004396	0.038372
L13.*return*	−0.002645	−0.016912*	−0.002383	−0.016945*
L14.*PUI*	−0.027870***	0.030371	0.002067	0.035899
L14.*return*	−0.001053	−0.010124	−0.00073	−0.010189
L15.*PUI*	0.012633	−0.071303**	0.007648	−0.068300*
L15.*return*	−0.004319	0.008298	−0.004142	0.008428
L16.*PUI*	−0.003352	−0.059361*	−0.010092	−0.058613*
L16.*return*	−0.001537	0.003303	−0.001354	0.003414
L17.*PUI*	−0.028285***	0.077680**	−0.035424***	0.071888**
L17.*return*	−0.004444*	0.017280*	−0.004329	0.017303*

* is significant at 10%, ** at 5% and *** at 1%

Table IX: VAR Results for windows 16 and 18

	3.75hr (15)		**4.00hr (16)**	
Lag	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$	$\boldsymbol{PUI_t}$	$\boldsymbol{return_t}$
constant	−0.002155***	−0.000199	−0.001924***	−0.000232
L1.*PUI*	0.010031	0.009690	0.012761	0.007043
L1.*return*	−0.003886	−0.026139***	−0.003920	−0.026116***
L2.*PUI*	0.000768	0.008938	0.003234	0.010825
L2.*return*	−0.002779	−0.000431	−0.002838	−0.000408
L3.*PUI*	0.021045**	−0.007769	0.025269***	−0.009434
L3.*return*	−0.003482	0.000235	−0.003450	0.000262
L4.*PUI*	0.009867	0.064634*	0.011975	0.064254*
L4.*return*	0.000906	0.023794**	0.000838	0.023747*
L5.*PUI*	−0.001023	−0.035586	0.000229	−0.032454
L5.*return*	−0.001162	0.002060	−0.001028	0.002024
L6.*PUI*	−0.011819	−0.033209	−0.008850	−0.034655
L6.*return*	−0.002127	−0.019226**	−0.001834	−0.019221**
L7.*PUI*	−0.031984***	−0.049437	−0.029251***	−0.048913
L7.*return*	0.001279	0.008287	0.001536	0.008306
L8.*PUI*	−0.016066*	0.029700	−0.011573	0.027104
L8.*return*	−0.000448	0.005398	−0.000564	0.005399
L9.*PUI*	−0.005754	0.076975**	−0.002056	0.080948**
L9.*return*	−0.001853	−0.012513	−0.001795	−0.012558
L10.*PUI*	−0.030787***	0.015785	−0.028179***	0.014915
L10.*return*	0.002835	0.017208*	0.002595	0.017220*
L11.*PUI*	−0.014898	0.045100	−0.010667	0.042258
L11.*return*	0.003386	−0.018351*	0.003366	−0.018324*
L12.*PUI*	−0.036536***	0.019919	−0.034233***	0.018199
L12.*return*	−0.000983	0.026728***	−0.001077	0.026746***
L13.*PUI*	−0.031250***	0.030934	−0.027195***	0.029044
L13.*return*	−0.002519	−0.016932*	−0.002523	−0.016950*
L14.*PUI*	−0.022529**	0.027905	−0.018029*	0.027662
L14.*return*	−0.001037	−0.010213	−0.000888	−0.010240
L15.*PUI*	−0.015316	−0.070816**	−0.010237	−0.070143**
L15.*return*	−0.004577*	0.008354	−0.004614*	0.008283
L16.*PUI*	−0.000724	−0.058172*	−0.025688***	−0.059754*
L16.*return*	−0.001758	0.003278	−0.002007	0.003302
L17.*PUI*	−0.026166***	0.077545**	−0.025177***	0.079665**
L17.*return*	−0.004501*	0.017200*	−0.004736*	0.017184*

* is significant at 10%, ** at 5% and *** at 1%

It is interesting to note that measuring the PUI over a 2-hour to a 4.5-hour gap yields 17 lags, indicating that a significant part of the market takes 4 hours and 15 minutes to respond to a change in the current political mood.

According to tables VI,VII,VIII and IX only at the 12,16 and 18 windows the return has a statistically significant lag over PUI (10%,5% and 10% p-values respectively) and only at lag 17, a sign that indeed the political uncertainty affects the market and not otherwise, since 4.5 hours later the market has already precified some of that information.

Further analysis shows that the US market return is not a random walk process when observed over a higher frequency such as the 15-minute tick and a AR(1) structure is not enough to describe the market. Although its' process are always significant when observing the first lag, all of the state specifications yield at least 5 different significant coefficients with the 3-hour lag having always a p-value of 1%, which means a big part of the market takes at least that amount of time to react.

The measurement proposed in this paper, PUI (9), shows significance in a 1 and 4-hour lag of at least 10%,5% significance respectively, thus being important to predict the $return_t$ process, and exhibiting that the window choice when specifying the index need not be exact. This behavior might come from the way that news venues have a different process, length-wise, over publishing.

On the 4-hour (16 window) time delta, the index shows significant responses at 1 hour (5%), 2 hours and 15 minutes (5%), 3 hours and 45 minutes (5%), 4 hours (10%), and, 4 hours and 15 minutes (5%). Since there is a concentration at 3:45 hrs to 4:15 hrs it shows that this is the average time most of the response is held, with the first two coefficients being negative and the last a positive correction, this reaction is indicative of the correction of earlier lags which mostly present a positive relationship as expected, showing that a positive (negative) forward uncertainty has a positive (negative) cumulative effect over the market return.

Interestingly, for all VAR(17) models the PUI relationship with SPY's return is mostly positive, with negative coefficients following mostly the biggest positive ones for each specification, further corroborating that indeed, negative shocks are mostly corrections/market reactions on the behavior as a whole.

Although the absolute value of the coefficients is small, at the 4 hrs model, considering that the maximum PUI in the dataset is 0.19, it would mean a 1.2$p.p.$ increase in the return in about 1 hour, which would mean about as much as a 40 points in the $S\&P500$.

D Impulse response function

The graphs for the impulse response functions (figure 6) for the 4 hours model shows that after the first hour a positive shock in PUI has a positive response from the market, followed by a negative trend from 1:15 hours to 2 hours, and then at 2.25 hours another positive response which is followed again by a correction from a shock in the PUI. In the last 30-minute gap, from 3:45 to 4:15 there is a big inverse movement which is an overshoot settling afterward.

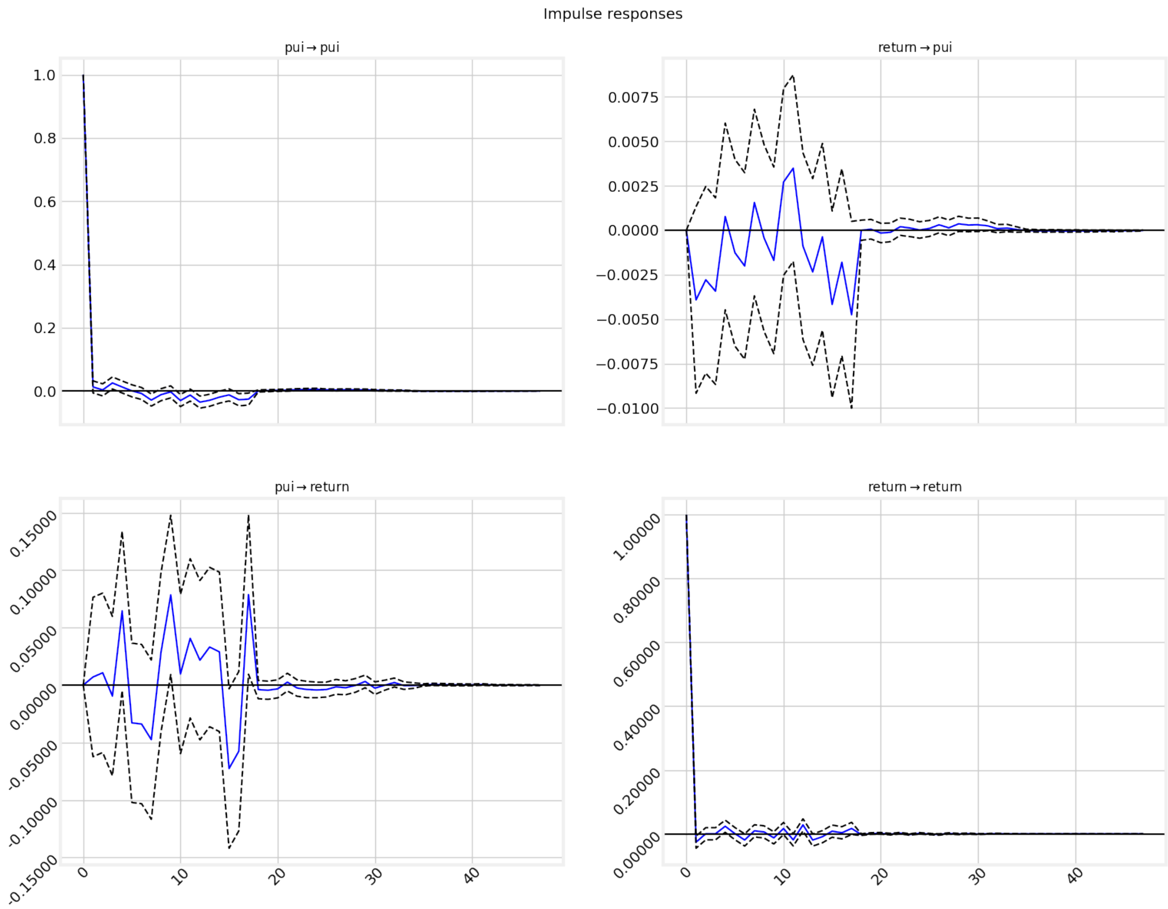

Figure 6: Impulse response function

For the cumulative responses (figure 7) it is also interesting to note that a positive shock on the return indeed has a positive effect on the whole market in the next hour, and a positive shock in PUI has also an impact that takes more than 6.5 hours to settle, showing a positive shock after an hour, followed by inverse movement from part of the market and then two more stages of positive shock and reaction starting at 2 hours and 15 minutes later and the last lag at 3 hours and 45 minutes.

The return shock on the PUI index shows inverse behavior, but with a higher degree of volatility with a small reaction at 2.5 hours before converging to the final cumulative shock value.

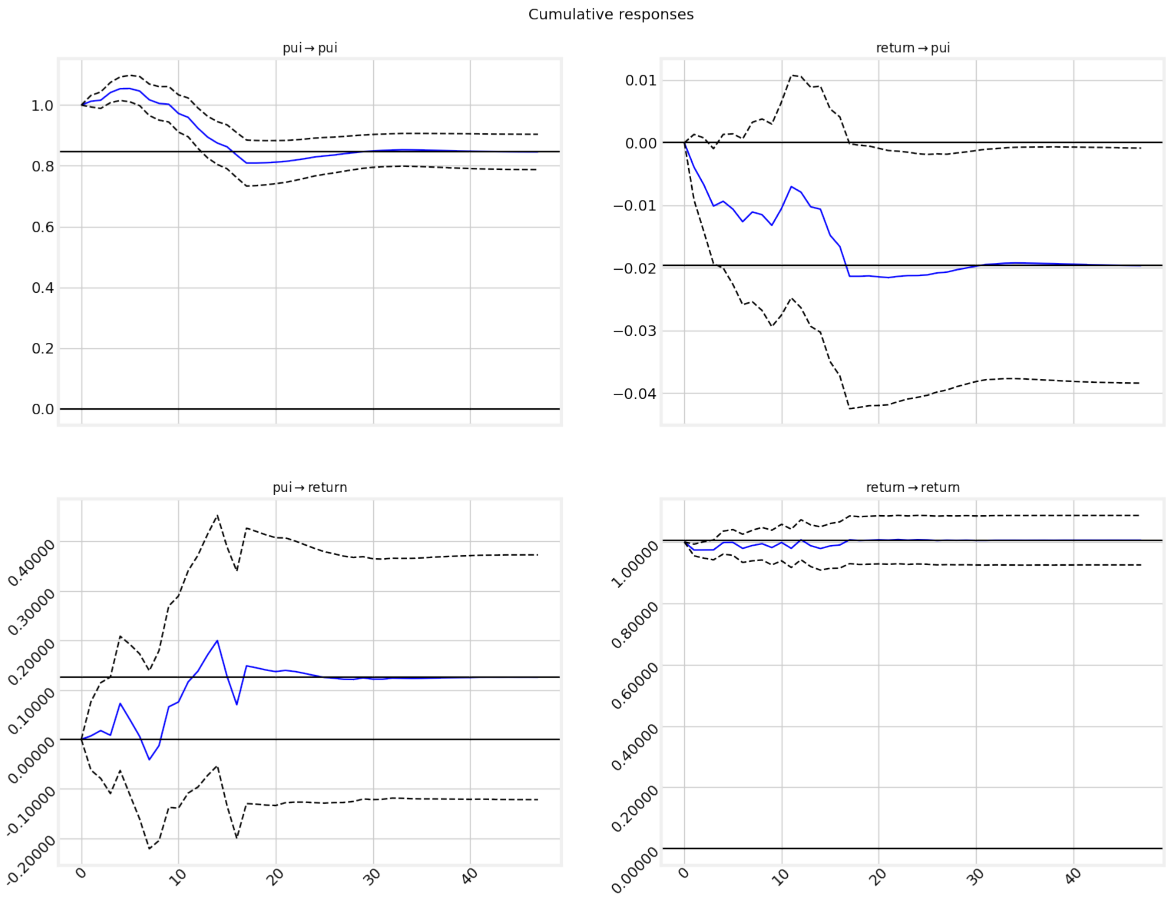

Figure 7: Cumulative impulse response

E Residual autocorrelation graphs

Figure 8, shows the same results as presented before on table V when discussing the lag-order selected by information criteria, and it is clear that there is no autocorrelation present in the residuals from the VAR(17) model considering a 16 periods window for PUI.

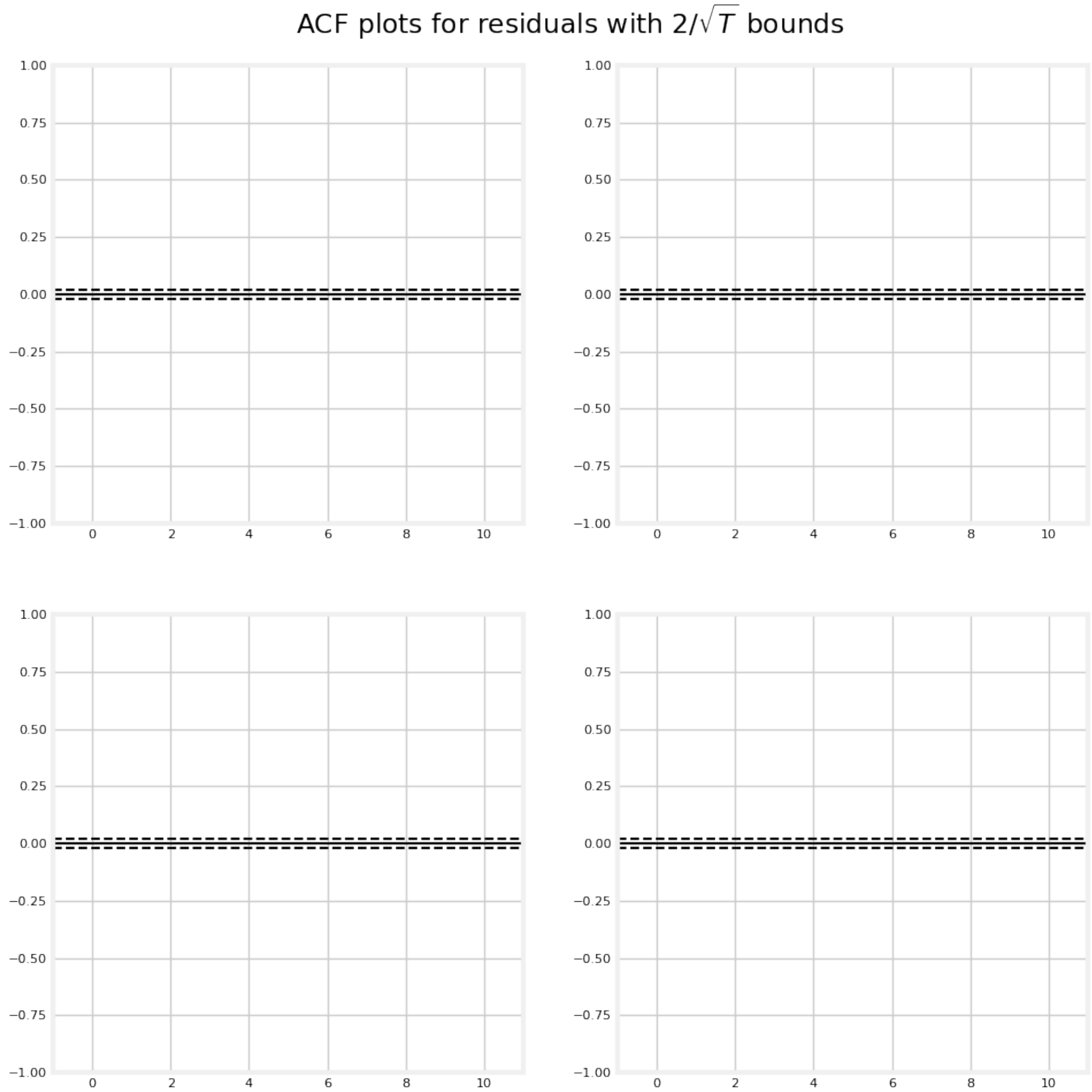

Figure 8: Autocorrelation of residuals

F *PUI versus VIX*

The Political Uncertainty Index could be representing some part of the volatility already in the VIX, even though it has a low correlation (figure 1), and thus it would not represent information orthogonal to economic factors.

To test if VIX takes temporal precedence over PUI, thus indicating if PUI is just a representation of the volatility test, the Granger Causality test results considering the 4 hours window is presented on table X, with the inverse test also being shown to assure PUI's orthogonality.

Table X: Granger Causality test p-values

	VIX towards PUI		PUI towards VIX	
Lag	***SSR F***	***Likelihood Ratio***	***SSR F***	***Likelihood Ratio***
1	0.743	0.743	0.503	0.503
2	0.822	0.822	0.284	0.284
3	0.909	0.909	0.295	0.294
4	0.912	0.912	0.440	0.440
5	0.875	0.875	0.582	0.581
6	0.933	0.933	0.700	0.699
7	0.879	0.878	0.787	0.786
8	0.898	0.898	0.857	0.857
9	0.838	0.837	0.614	0.613
10	0.851	0.850	0.472	0.470
11	0.868	0.867	0.554	0.552
12	0.900	0.899	0.651	0.649
13	0.909	0.909	0.601	0.599
14	0.934	0.934	0.632	0.630
15	0.607	0.604	0.658	0.656
16	0.608	0.605	0.704	0.701
17	0.471	0.468	0.670	0.668
18	0.541	0.538	0.678	0.675
19	0.570	0.566	0.729	0.727
20	0.462	0.459	0.648	0.644
21	0.466	0.462	0.708	0.705
22	0.469	0.465	0.688	0.684
23	0.516	0.511	0.735	0.731
24	0.420	0.415	0.749	0.746
25	0.474	0.469	0.795	0.792
26	0.543	0.537	0.795	0.792

* is significant at 10%, ** at 5% and *** at 1%

The results presented in table X indicate that there is not a granger-causality process in either way over a trading day's period, with similar results on testing up to 72 lags.

V Conclusion

Although Hall (1978) shows why returns should behave in a random walk, with a sound theory, it seems that taking this affirmative under a microscope doesn't hold. With the availability of higher frequency data, this ought to be debunked at least in a very small frequency, due to the nature of humanity. The market can't react as fast as the information is generated, as even with automated trading there is a large part of market participants that makes decisions in such a way that their information set is not updated instantaneously.

Furthermore, the main goal of this study is to analyze the influence of politicians in the US market (specifically the SPY index) and over that subject, the results show that it takes from 1 hour for the market to react to noises converging just after 6.5 hours, be it a negative or a positive indication from the political arena. Also, it follows the expected positive reaction to positive noises, indicating indeed a change over risk evaluation.

The *Politcs Uncertainty Index* framework shows some promise as being used as an indicator, but it blindly accepts all inputs and further research to determine the specific channels or tone from media outlets over which brings the most information relevant to the market is needed, but the goal was to set a precedence of **if** and **when**, in a high-frequency environment, the PUI can bring new information, orthogonal to the information available in lagged price levels, and it shows significative indicators for doing so and being used in other studies.

The similar results to different specifications are in line with the news becoming public at a slightly different time from each media outlet, thus for a better understanding, it might be needed to properly categorize news themes and measure their spread across time.

The cumulative responses also show that the PUI causes a reaction after an hour with two more spikes being corrected at the end of each with convergence being achieved at around 6 hours and 30 minutes for SPY.

References

Acemoglu, D., Hassan, T. A., and Tahoun, A. (2018). The power of the street: Evidence from egypt's arab spring. *The Review of Financial Studies*, 31(1).

Arbatli, E. C., Davis, S. J., Ito, A., et al. (2017). Policy Uncertainty in Japan. *IMF Working Paper No. 17/128.*

Baker, S. R., Bloom, N., Canes-Wrone, B., Davis, S. J., and Rodden, J. (2014). Why has US Policy Uncertainty Risen Since 1960? *American Economic Review*, 104(5):56–60.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Bekaert, G., Harvey, C. R., Lundblad, C. T., and Siegel, S. (2016). Political Risk and International Valuation. *Journal of Corporate Finance*, 37:1–23.

Brogaard, J. et al. (2020). Global Political Uncertainty and Asset Prices. *The Review of Financial Studies.*

Cochrane, J. H. (2005). *Asset Pricing: Revised Edition.* Princeton University Press.

Cochrane, J. H. (2011). Presidential address: Discount rate. *Journal of Finance*, 66(4).

Diamonte, R. L., Liew, J. M., and Stevens, R. L. (1996). Political Risk in Emerging and Developed Markets. *Financial Analysts Journal*, 52(3):71–76.

Dugast, J. (2018). Unscheduled News and Market Dynamics. *Journal of Finance*, 73(6).

Franses, P. H. and Hobijn, B. (1998). Increasing seasonal variation; unit roots versus shifts in mean and trend. *Applied stochastic models and data analysis*, 14(3):255–261.

Goldstein, J. S. (1992). A Conflict-Cooperation Scale for WEIS Events Data. *Journal of Conflict Resolution.*

Hall, R. E. (1978). Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence. *Journal of Political Economy.*

Hansen, L. P. and Richard, S. F. (1987). The Role of Conditioning Information in Deducing Testable Restrictions Implied by Dynamic Asset Pricing Models. *Econometrica: Journal of the Econometric Society*, pages 587–613.

Kelly, B., Pástor, L., and Veronesi, P. (2016). The Price of Political Uncertainty: Theory and Evidence from the Option Market. *Journal of Finance*, 71(5).

Kilian, L. and Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.

Lochstoer, L. A. and Tetlock, P. C. (2020). What Drives Anomaly Returns? *Journal of Finance*, 75(3).

Pástor, L. and Veronesi, P. (2013). Political Uncertainty and the Risk Premia. *Journal of Financial Economics*.

Pérez-Liñán, A. (2007). *Presidential Impeachment and the New Political Instability in Latin America*. Cambridge University Press.

Ward, M. D., Beger, A., Cutler, J., Dickenson, M., Dorff, C., and Radford, B. (2013). Comparing GDELT and ICEWS event data. *Analysis*, 21(1):267–297.