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1 Introduction

> ”*That economic decisions are made without certain knowledge of the consequences is pretty self-evident. But, although many economists were aware of this elementary fact, there was no systematic analysis of economic uncertainty until about 1950.*”
>
> *Kenneth Arrow*

The issue of uncertainty is a central one in the study of economics, as the quote above suggests. This is because in the economic world every single decision, from the smallest to the biggest one, is made in condition of uncertainty. For example, when uncertainty is high, individuals and institutions tend to postpone big decisions, and become more conservative, saving more and consuming less.

These are all intuitive observations, but the aim of this work is instead to dig a little deeper, and try to find out how uncertainty can be measured (and which type of uncertainty is measured) in different ways, synthesized in various indexes. Then, we are going to find out through statistical analysis how Monetary Policy decisions affect the level of uncertainty in the economy.

This is a crucial question, as the reasoning for the implementation of Monetary Policy decisions is often that of smoothing the fluctuations of the business cycle, thus reducing uncertainty for the economic agents and therefore increasing the potential for growth through stabilization. Therefore, proving that Monetary Policy influences the level of uncertainty in the economy is paramount to justify its use in the first place.

Now that we have stated the aim of our work, we will continue with this brief introduction, defining what Uncertainty means, presenting some indices for measuring Uncertainty, then going on to describe how Monetary Policy works and which indices we will use to measure it.

1.1 What Uncertainty Means, and How to Measure it

We should start our discussion by understanding what Uncertainty really is about. In particular, it's important to differentiate clearly the concept of risk from the concept of uncertainty. As American economist Frank Knight put it:

> *"Uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated. [...] It will appear that a measurable uncertainty, or "risk" proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all."*[4]

This quote defines what is known in economics as "Knigthian Uncertainty", and can be summarized with another simple quote:

> "*You cannot be certain about uncertainty.*"

This definition could lead us to conclude that it is not possible to investigate the dynamics of uncertainty, as it, by definition, cannot be measured. Luckily, this is far from the truth. Even if measuring uncertainty itself is obviously impossible without acquiring more information, we can measure the level of uncertainty in a given time.

Of course, it's not a simple process, as uncertainty cannot be measured directly and you need to better define which type of uncertainty you are looking for. Nevertheless, measuring the level of uncertainty and its dynamics through indexes that serve as proxies for the level of uncertainty in an economy is possible, as we will see in the following pages.

Before that, it's important to acknowledge how research on uncertainty has recently seen a surge in interest, especially after the Great Recession in 2008. This increase in research concerning economic uncertainty is explained by Nicholas Bloom as driven by several factors (see [2] for details). First, the high uncertainty generated by the 2008 financial downturn and its role in shaping the subsequent recession has focused policy attention on the topic. Second, the increased availability of empirical proxies for uncertainty (such as the ones we are going to see in a moment) has facilitated empirical research by economists. Last, but not least, the increase in computing power has made it possible to include shocks in the level of uncertainty into a wide range of economic models. So far, the research has made substantial progress, but lots of questions remain unanswered, especially about the measurement, cause and effect of uncertainty.

Economic literature also highlights four major mechanisms through which recessions might increase uncertainty. First, when business is good, firms trade actively with each other, thus creating a continuous flow of information between them that is weakened when recession hits and trade grinds to a halt, thus stopping the process of acquiring information through trade and increasing overall uncertainty about the future. Second, individuals are more confident in predicting the future when the overall sentiment in the economy is "business as usual", particularly in a growing economy; also, recessions are (luckily) rarer than periods of sustained growth, therefore people are less used to dealing with them and not so confident in their predictions, thus increasing uncertainty. Third, public policy is usually stable in periods of growth, and unstable or hyperactive in periods of recession, fueling uncertainty.

Another important aspect to consider is that economic research has found evidence that lower-income countries experience higher median values of uncertainty. The possible reasons may be various, starting from the fact that developing countries tend to have less-diversified economies, often dependent on the export of a small variety of products. Furthermore, those products they focus on are often characterized by highly volatile prices; commodities like rubber, sugar, oil and copper could be examples of this phenomenon. Lastly, let's not forget that developing countries tend to have more domestic political shocks like violent coups, revolutions and civil wars, and are more vulnerable to natural disasters. All of these factors (and probably many others) bring the overall economic uncertainty levels of developing countries to one third higher than the level of developed countries, according to some estimates.

These results can help us consider that, while measuring the level of uncertainty can be a difficult but straightforward procedure, untangling the complicated web of causes and effects, historical and cultural, which bring a particular country in a particular period of history to have an high level of uncertainty, is much more difficult.

Nevertheless, even if in much more simple fashion, we are going to try. Throughout the following sections, we are going to present the various indexes we are going to look at in order to investigate the relationship between Monetary Policy and fluctuations in the level of uncertainty, beginning with a general measure of Economic Uncertainty: the EPU.

1.1.1 The Economic Policy Uncertainty Index (EPU)

One of the indexes we use is a proxy for general Economic Policy Uncertainty, called EPU, as calculated by Baker, Bloom and Davis (see [1] for details). As they explain in their paper, the index reflects the frequency of articles in 10 leading US newspapers that contain a certain set of terms. For general EPU for example, the terms searched are "economic/economy", "uncertain/uncertainty" and one or more between "Congress","deficit","Federal Reserve", "legislation", "regulation" or "White House". The index is also calculated specifically for some policy categories, such as Government Spending, Financial Regulation, Taxation, and many others (each with specific sets of key words to search for).

The aim of this measure in the words of its creators is:

> "*To capture uncertainty about **who** will make economic policy decisions, **what** economic policy actions will be undertaken and **when**, and the economic **effects** of policy actions (or inaction) - including uncertainties related to economic ramifications of "non economic" policy matters, for example military actions.*"

Obviously, this approach to the measurement of EPU can raise potential concerns about newspapers' reliability, but the EPU shows a strong correlation with other types of measures of economic uncertainty, such as implied stock market volatility (58% correlation with VIX for the EPU at large, and 73% if we take into consideration Financial EPU only). Also, the index can be calculated as either a human-generated or computer-generated result, with high correlation between the two methods, further strengthening the accuracy of this index.

The authors also did a test in order to verify if political slant in newspaper coverage could influence the measurement of EPU: they split their 10 newspapers into the 5 most Republican leaning and the 5 most Democratic leaning, and found that the two resulting indices presented a correlation of 92%, suggesting that political slant does not seriously distort variation over time in newspaper coverage of EPU and therefore is not a major concern for the accuracy of the index.

In their paper the authors provide also numerous proofs of the utility of this particular uncertainty measure, like showing that firms with greater exposure to government purchases tend to experience greater stock price volatility in times of higher EPU; firms in the defense, health care and financial sectors are also especially responsive to their own category-specific EPU, confirming the information value of the specific categories as well.

The paper goes on to explain how policy uncertainty may retard investment, hiring and growth in policy-sensitive sectors like the one mentioned before. In the end, according to the authors the results suggest that elevated policy uncertainty in the US and the EU in recent years may have harmed macroeconomic performance.

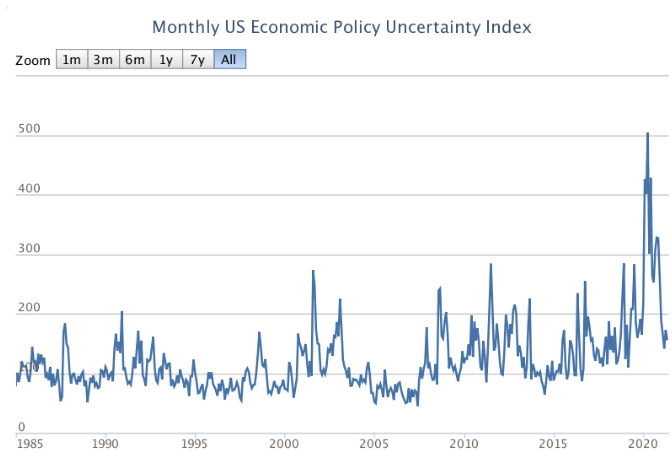
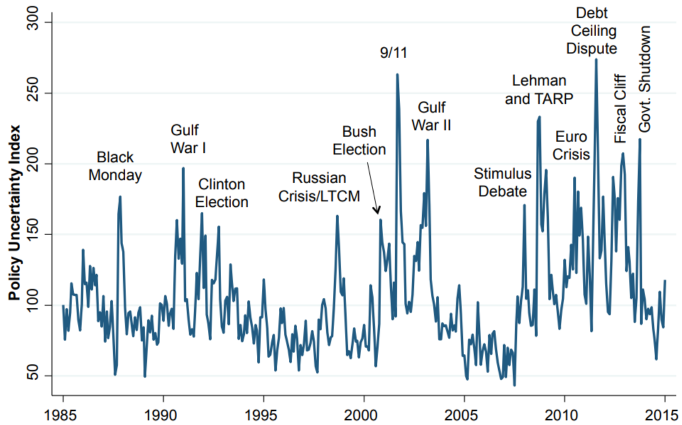


Figure 1: *Graph showing the level of Monthly EPU in the US, from 1985 to 2021; we can clearly see an upward trend, especially in the second half of the 2010s*

If we look at those two graphs, in Figure 1 we see how EPU moved in the period between 1985 and 2021, showing a clear upward trend from 2008 onward, especially in the second half of the 2010s, which are characterized by an higher mean value of EPU, especially when confronted with the low-EPU 1990s.



Notes: Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more policy relevant terms: 'regulation', 'federal reserve', 'deficit', 'congress', 'legislation', or 'white house'. The series is normalized to mean 100 from 1985-2009 and based on queries run on 2 February, 2015 for the USA Today, Miami Herald, Chicago Tribune, Washington Post, LA Times, Boston Globe, SF Chronicle, Dallas Morning News, NY Times, and the Wall Street Journal.

Figure 2: *Graph showing the level of Monthly EPU in the US, from 1985 to 2015, with all the respective events which caused big spike in the index*

In Figure 2 instead we can see how different events caused spikes in the EPU index; for example both US elections in which the incumbent lost, in 1992 and in 2000; also 9/11 and the Gulf War, or the 2008 financial crisis.

One interesting aspect to point out is the fact that not all spikes are associated with general economic downturn; for example the Russian Crisis in 1998 is not linked to a recession or a financial crash; the same can be said for the stimulus debate in 2007 or the government shutdown debate in 2014. This teaches us that the EPU measures the people's state of worry about economic uncertainty, and not uncertainty per se. Thus, not all fluctuations in EPU are created equal, and not all of them could cause similar effects on the economy at large.

1.1.2 The VXO Index

The second index we are going to use in our work is the VXO Index, more specifically *CBOE S&P100 Volatility Index*, commonly known also as the "Fear Index". The idea upon which the index is constructed is to measure the stock market's expectation of volatility based on S&P100 index options. It is calculated on a real-time basis by the CBOE (the *Chicago Board Options Exchange*), starting in 1986. Today, another similar index is often brought up as an alternative to the VXO: the VIX, which looks at the S&P500 index instead, but with a similar procedure. In fact, originally the VXO was named itself VIX, but when a new methodology for computing the index was proposed, the original method was renamed as the VXO.

Technically, the VXO is a 30-day expectation of volatility given by a weighted portfolio of at-the-money European Options on the S&P100. Firstly, let's quickly explain what an option is; the definition for options is the following:

> "Options are derivative contracts which attribute to the buyer the right to buy or sell an underlying asset at a certain strike price and at a certain date (or before that date)."

Option are asymmetric contracts, because only the seller is obligated to satisfy the buyer's right to buy or sell the asset. The basic elements of an option are:

- the **underlying asset**: the asset used as the object of the option
- the **faculties**: options which give the buyer the right to buy are known as *call*, and options who give the buyer the right to sell are known as *put*
- the **expiration date**: options which give the buyer the right to buy or sell exclusively on the expiration date are called *European Options*, and options which give the buyer the right to buy or sell in every date prior to the expiration date are called *American Options*
- the **strike price**: it is the price at which the buyer can take advantage of its right to buy or sell the asset

Knowing this we can finally look at the equation used to calculate the VXO index, as shown here below:

$$VXO = \sqrt{\frac{2e^{r\tau}}{\tau}\left(\int_0^F \frac{P(K)}{K^2}dK + \int_F^\infty \frac{C(K)}{K^2}dK\right)}$$

where τ is the number of average days in a month (30 days), r is the risk-free interest rate, F is the 30-day forward price expectation on the S&P100 and $P(K)$ and $C(K)$ are prices for puts and calls (of the European type) with strike price K and 30 days until maturity.

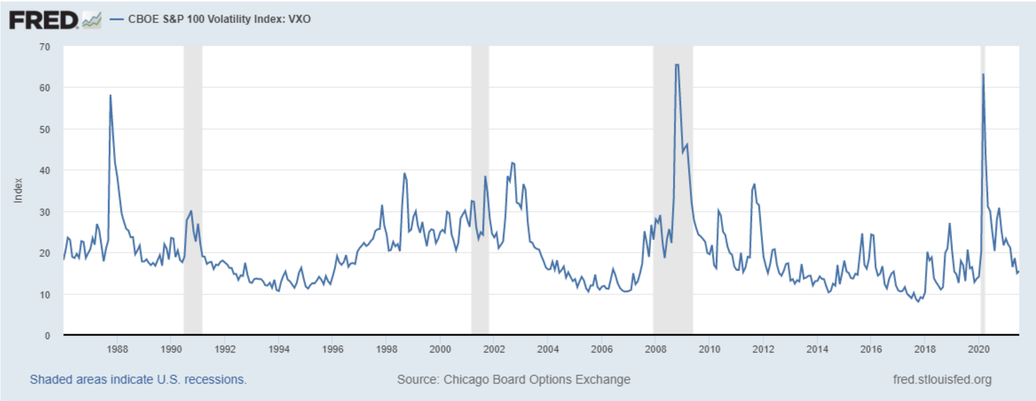


Figure 3: *Graph showing the level of monthly VXO in the period from 1986 to 2021*

As we stated before, the VXO and the EPU are correlated, as EPU contains some of the information contained also in the VXO: in fact, the financial EPU is more closely correlated with the VXO, with a correlation of 73%; we can say that they are pretty interchangeable.

Let's not forget however that the underlying phenomenon measured by the VXO is quite different from the one measured by the EPU, so they are not bound to move in the same direction. Furthermore, let's remark the fact that the VXO is a measure of uncertainty over a defined time horizon (30 days), while the EPU has no defined horizon to measure uncertainty.

1.2 How Monetary Policy works

Monetary Policy is one of the tools that economic policy makers have at their disposal in order to smooth the fluctuations of the business cycle, and so, in theory, reduce overall economic uncertainty and favour economic growth.

In advanced market economies such as the US, Monetary Policy is a faculty of the Central Bank, which is autonomous from the executive power in order to have more credibility on the financial markets. In the American Monetary System, the CB (the Fed) uses Monetary Policy to control the supply of money to the overall US economy, but this isn't done by simply printing banknotes or destroying them.

In fact, the main instrument the Fed has for controlling the Money supply is setting the so-called *overnight interest rate*, the interest rate at which all banks in the Federal Reserve system can lend money to each other or deposit it in the Fed's account. We will explain this tool later in more detail.

For now, what we need to know is that the Fed usually follows a so-called Taylor Rule when deciding the level of overnight interest rate at a given time; sometimes, anyway, the interest rate deviates from the one which would be determined by the Taylor Rule, as we will explain in a moment. A deviation of this type cannot be forecasted by market participants, and it is therefore called a "Monetary Policy Shock". In the following section we will see one way to measure Monetary Policy Shocks for the US economy.

1.2.1 The proxy for Monetary Policy Shocks (MPI_t)

This is the third index we use in this work; it's a proxy variable for Monetary Policy Shocks calculated by Silvia Miranda-Agrippino and Giovanni Ricco (see [5] for details). In their paper, they estimate a Monetary Policy Shocks variable in the period going from 1990 all the way to 2009. But how is it calculated?

The paper starts by outlining a simple model of noisy information, explaining that there are two important implications of having a model with imperfect information. First, average expectations respond more gradually to shocks to fundamentals than do the variables that are being forecasted; this means that the revision of expectations by market participants can be correlated over time, and contain information about current and past structural shocks. Secondly, due to the asymmetry of information between policy makers and market participants, policy actions can convey information about the fundamentals.

Knowing this, they proceed considering an economy with a k-dimensional vector of macroeconomic fundamentals; evolving according to an autoregressive process as shown in the equation below:

$$x_t = \rho x_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sum \varepsilon_t)$$

Where ε_t is defined as the vector of structural shocks. Every single period is divided into an opening stage $\underline{t}$ (the period when shocks are realised) and a closing one $\bar{t}$. Agents and CBs do not observe the vector directly, rather they form expectations about x_t (through a so-called *"Kalman Filter"*) based on the private noisy signals they possess. We denote with $s_{i,\underline{t}}$ and $s_{cb,\underline{t}}$ the signals received at $\underline{t}$ by investors and the CB respectively. In a similar fashion, we use $F_{i,\underline{t}}$ and $F_{cb,\underline{t}}$ to denote their forecasts on the fundamentals. In the model, investors trade securities based on i_{t+h}, the realisation of the policy rate at time $t+h$ (where h is the investment horizon). The price of a futures contract at this rate reflects the investors' aggregate expectations, as follows:

$$p_{\underline{t}} = F_{\underline{t}} x_{t+h} + \mu_t$$

where μ_t is a stochastic component, such as the risk premium. At $\bar{t}$, the CB sets the policy rate using a Taylor Rule in the form

$$i_t = \varphi_0 + \varphi_x^{'} F_{cb,\underline{t}} x_t + u_t + w_{t|t-1}$$

where u_t denotes the monetary policy shock, and $w_{t|t-1}$ represent the possible announcement (or leak) at time $t-1$ of a deviation from the Taylor Rule by the CB taking place at time t. This distinction serves in order to clean the monetary policy shock component from those deviations from the Taylor Rule who are not shocking, as they are expected by the market.

Based on these deviations, agents update their forecasts and trade at time $\bar{t}$. Conditional on i_{t-1}, observing the interest rate is equivalent to getting a public signal with common noise ($\bar{s}_{cb,\bar{t}}$) from the CB. Because of this, the price of future contracts is revised in proportion to the average revision of market expectations, following

$$p_{\bar{t}}(i_{t+1}) - p_{\underline{t}}(i_{t+1}) \propto (F_{\bar{t}} x_{t+1} - F_{\underline{t}} x_{t+1})$$

In conclusion, the paper states that following a CB policy announcement, information about economic fundamentals can be transferred from the CB to the market participants, who update their set of information based on CB policy announcements, extracting signals about the structural shocks ε_t.

In order to estimate Monetary Policy shocks in the US, the paper uses the fourth federal funds futures ($FF4$); specifically, the intraday movement in the $FF4$ contracts that are registered within a 30-minute window surrounding the time of the FOMC announcements. FOMC stands for *Federal Open Market Committee*, a committee within the Fed, charged with overseeing the nation's open market operations. The calculation is made in the period between 1990 and 2009.

One concern of the authors lies in the role of unscheduled meetings of the FOMC, as they usually happen when urgent decisions are made in times of particular economic distress. Therefore, they try to use market surprises registered around scheduled meetings only, finding that results are robust; the problem is that there are only 8 scheduled meetings in each year, and this creates missing values in the regression (and we will see how this can be a limiting factor in our analysis).

Another concern arises as the need to account for information frictions in the economy, such as the slow absorption of information in the economy. To account for this, they follow a three-step procedure: first, they project high-frequency market-based surprises in the $FF4$ around FOMC announcements on Greenbook forecasts and forecasts revisions for real output growth, inflation and the unemployment rate. They run the following regression at FOMC meeting frequency:

$$FF4_m = \alpha_0 + \sum_{j=-1}^{3} \theta_j F_m^{cb} x_{q+j} + \sum_{j=-1}^{2} \upsilon_j [F_m^{cb} x_{q+j} - F_{m-1}^{cb} x_{q+j}] + MPI_m$$

The forecast horizon is denoted in quarters, and q denotes the current quarter. This first step delivers as a residual an instrument for Monetary Policy shocks (MPI_m).

As a second step, they construct a monthly instrument by summing the daily MPI_m within each month.

As the final third step, they account for the slow absorption of information by removing the autoregressive component in the monthly surprises; the resulting MPI_t is the residual of the following regression

$$\overline{MPI_t} = \varphi_0 \sum_{j=1}^{12} \varphi_j \overline{MPI}_{t-j} + MPI_t$$

In months without meetings, MPI_t is equal to zero.

This MPI_t is the index we are going to use as a proxy for Monetary Policy shocks in the US. As we have previously stated, the index is not continuous, as the FOMC does not meet in each month, and this will likely cause problems in our attempt at identifying monetary policy effects on Economic Policy Uncertainty, as we will be seeing soon.

1.3 Analysing Data

From now on, we will discuss the results of our analysis on the various indices we presented. Obviously, we cannot report here all the code we wrote in R Studio and that we used in order to carry out the work.

Therefore, the code and all the references, with the various time series can be easily found at this **link**, in the case somebody reading this work needs to look at the methodology and the specific coding solutions used, or wants to try to replicate the results we are going to examine in the following pages.

2 Do Monetary Policy Shocks Matter?

2.1 The procedure

Now that we've laid out all of the ingredients for our simple research, we can start analysing our procedure. Our aim, as we previously stated, is to find the effects of Monetary Policy decisions on the overall Economic Policy Uncertainty in the US, examining the period going from 1991 to 2009 (this is because our proxy is calculated in that specific time frame only); to do this we will use a very simple linear regression model:

$$EPU_t = \beta_0 + \beta_1 EPU_{t-1} + \beta_2 u_t + \beta_3 MP_t + \varepsilon_t$$

Where EPU is the Economic Policy Uncertainty index, EPU_{t-1} is its first lag, u_t is the unemployment rate in the US at time t (used as a control variable), and MP_t is the proxy for monetary policy shocks in the US.

By doing this regression, we hope to find if Monetary Policy shocks in the US (as defined before) influence the EPU index, and how. We have included the EPU's first lag to account for autocorrelation in the time series, and the US unemployment rate in the regression as a control variable. In fact, the unemployment rate could affect EPU in significant ways, as the index is derived from newspapers, which sentiment on the state of the economy could be negatively linked to the unemployment rate.

What we expect to find is a positive and significant coefficient for both the lag on EPU and the unemployment rate, as both should influence positively the level of EPU in a given month. In fact, an high EPU in the previous month should reverberate in the next one, and an high unemployment rate should enhance the impression of living in uncertain economic times, sparking news coverage in the press and increasing EPU level. However, we can't say anything *a priori* on what the coefficient of the Monetary Policy shock proxy should be, as this is what we are trying to infer. In fact, there could be compelling evidence in favor of a positive coefficient or even a negative one, or perhaps no effect at all on the level of EPU. Let's see then how the results on this simple regression turned out.

2.2 First regression results

When we analyse our data using R Studio, what we find is as shown in Table 1 below.

Table 1: *First regression, with the first lag of EPU, the unemployment rate and the monetary policy shock proxy as explanatory variables*

	Dependent variable:
	EPU
Lag(EPU, 1)	0.700***
	(0.056)
UNEMPLOYMENT	3.091**
	(1.547)
PROXY	−9.405
	(34.190)
Constant	9.805
	(7.661)
Observations	227
R^2	0.617
Adjusted R^2	0.612
Residual Std. Error	24.653 (df = 223)
F Statistic	119.929*** (df = 3; 223)
Note:	*p<0.1; **p<0.05; ***p<0.01

At first glance these results don't look so bad, as both the first lag of EPU and the unemployment rate seem to be significant in explaining EPU behaviour in the period from 1991 to 2009; also, as we expected, they are both positive in sign. The problem lies with the estimated coefficient for the monetary policy proxy itself, which exhibits an enormous standard error, making the regression not significant in any way (the coefficient could be either negative, positive or null).

One reason could be that our time frame is not perfect; the period from 1991 to 2007 is very different in terms of EPU level from the last two years in the time series, 2008 and 2009, particularly because of the start of the Financial Crisis in 2008, and this could potentially undermine our results.

Therefore, we can try to end our time series in December 2007, leaving out 2008 and 2009; let's see how results are influenced by this change in Table 2.

Table 2: *New time frame: 1991-2007*

	Dependent variable:
	EPU
Lag(EPU, 1)	0.669***
	(0.068)
UNEMPLOYMENT	5.148**
	(2.145)
PROXY	4.515
	(29.395)
Constant	1.005
	(9.739)
Observations	203
R^2	0.625
Adjusted R^2	0.619
Residual Std. Error	23.088 (df = 199)
F Statistic	110.328*** (df = 3; 199)
Note:	*p<0.1; **p<0.05; ***p<0.01

Here we see that, even if the standard error on the Monetary Policy shocks proxy is smaller, it's not nearly enough to make the estimate even remotely significant; we must therefore hypothesize different ways to investigate the impact of Monetary Policy Shocks on US uncertainty.

2.3 Using the VXO Index

One possible way is to switch the EPU index with the VXO index, which as we previously explained is an indicator of implied stock market volatility (for the US stock market). The new regression model therefore will be as follows:

$$VXO_t = \beta_0 + \beta_1 VXO_{t-1} + \beta_2 u_t + \beta_3 MP_t + \varepsilon_t$$

By using the VXO instead of the EPU, we expect to get better results, as the VXO should be even more influenced by Monetary Policy Shocks such as those captured by the proxy we are examining.

Using this new model, the resulting regression is described in Table 3.

Table 3: *Here we use VXO as dependent variable instead of EPU*

	Dependent variable:
	VXO
Lag(VXO, 1)	0.912^{***}
	(0.030)
UNEMPLOYMENT	-0.340^{***}
	(0.125)
PROXY	2.108
	(3.184)
Constant	3.743^{***}
	(0.980)
Observations	227
R^2	0.826
Adjusted R^2	0.823
Residual Std. Error	3.816 (df = 223)
F Statistic	352.354^{***} (df = 3; 223)
Note:	*p<0.1; **p<0.05; ***p<0.01

We can see that the standard error on the Proxy variable is sensibly smaller, but still not enough to be significant; all the other coefficients are significant with three degrees and the R^2 is at 82% so the regression is in general pretty good, but it seems that the proxy doesn't explain fluctuations in market volatility sufficiently, or at least not for this sample. One interesting detail, anyway, is represented by the sign of the unemployment rate's coefficient; in this case it is negative, probably because unemployment (and the economy at large) takes time to be affected by fluctuations in stock market volatility and therefore is not in sync with the VXO.

We can try to use the same strategy we chose before, cutting the sample in two parts, precisely in December 2007, in order to mitigate the effects of including the Financial Crisis of 2008 in our analysis. The results are shown below in Table 4.

Table 4: *Results for the period 1991-2007*

	Dependent variable:
	VXO
Lag(VXO, 1)	0.894^{***}
	(0.042)
UNEMPLOYMENT	-0.479^{**}
	(0.197)
PROXY	2.457
	(3.249)
Constant	4.657^{***}
	(1.579)
Observations	203
R^2	0.838
Adjusted R^2	0.836
Residual Std. Error	2.913 (df = 199)
F Statistic	343.280^{***} (df = 3; 199)
Note:	*p<0.1; **p<0.05; ***p<0.01

Contrary to what we expected, cutting the sample at the end of 2007 increases the error on the coefficient for the proxy, undermining the theory that data from 2008 onward damages our regression in this specific case. One explanation could be that our proxy, as we previously described, is not calculated each month. Instead, the proxy has an assigned value of 0 for every single month in which the FOMC (*Federal Open Market Committee*) is not in session. This unfortunately creates holes in our proxy time series, which could be reflected in a bigger standard error, especially as we have so few observations to begin with. In fact, from 1991 to 2009 we have only 227 observations, so considering that on average the FOMC meets 8 or 9 times a year, we see that we have considerably less data for the proxy than we have for our other variables in the regression, and this could impact the reliability of the estimator. In fact, this could explain why cutting the sample worsened the standard error: the problem stems from the fact that we don't have enough data.

However, there's another possible explanation we need to take into consideration; it's possible that Monetary Policy shocks don't explain at all the fluctuations in US uncertainty measured by the EPU and the VXO, and that the effects of monetary policy decisions on uncertainty may be explained by Systematic Monetary Policy. Let's investigate this possibility in the following section.

3 Does Systematic Monetary Policy Matter?

3.1 A new hypothesis

Our new working hypothesis now is that, if the EPU and the VXO are not affected in any significant way by Monetary Policy, as our regression results seem to indicate, maybe systematic Monetary Policy decisions are the answer to uncertainty fluctuations in the US. This new hypothesis raises a pretty important question: is systematic Monetary Policy effective in dealing with uncertainty, or not? Perhaps, could it even fuel it?

To test our hypothesis, we can change our regression to use, in substitution of our proxy for monetary policy shocks, the time series for interest rates on US Treasury Bonds with 10 years until maturity, which we will call from now on $DGS10$. We can try to regress this time series both on EPU and on VXO.

The $DGS10$ is not directly set by the Fed, rather it's influenced by the forces of supply and demand through an auction mechanism on the Treasury Bond secondary market. When the demand for Treasury notes goes up, the price goes up too; the bill rate remains fixed, so the yield on the bill goes down. The opposite is also true; whenever demand is low, the bill rate being equal, prices go down and yields therefore go up.

Of course, the $DGS10$ not being set directly by the Fed, it can't be a direct indicator of systematic Monetary Policy actions; anyway, we can use it as a proxy as it is directly influenced by the Fed's decision on the level of Federal Funds Rate to set. Also, it is not undermined by the zero lower bound problem, whereas the Federal Funds Rate is, especially from 2008 onward.

3.2 Monetary Policy effects on EPU

Let's start with the first regression model, with EPU as the variable under study:

$$EPU_t = \beta_0 + \beta_1 EPU_{t-1} + \beta_2 u_t + \beta_3 DGS10_t + \varepsilon_t$$

We can see the output of the first regression model in Table 5 below.

Table 5: *Here we substitute the proxy with the DGS10*

	Dependent variable:
	EPU
Lag(EPU, 1)	0.702***
	(0.055)
UNEMPLOYMENT	3.019*
	(1.590)
DGS10	−0.795
	(1.503)
Constant	14.337
	(11.650)
Observations	227
R^2	0.618
Adjusted R^2	0.613
Residual Std. Error	24.636 (df = 223)
F Statistic	120.200*** (df = 3; 223)
Note:	*p<0.1; **p<0.05; ***p<0.01

In this first case we can see that $DGS10$ is not significant in explaining the fluctuations in EPU; also, the R^2 is lower than previous regression, at only 61%. Looking at this first regression we can say that $DGS10$ does not significantly affect EPU. Reducing the time frame does not make the results better either (for the sake of brevity, we are not going to report here the results of those subsequent regressions).

3.3 Monetary Policy effects on VXO

Let's then look at a second regression model, studying VXO instead

$$VXO_t = \beta_0 + \beta_1 VXO_{t-1} + \beta_2 u_t + \beta_3 DGS10_t + \varepsilon_t$$

The result of the regression using the second model are instead found in Table 6.

Table 6: *Here the variable under study is VXO*

	Dependent variable:
	VXO
Lag(VXO, 1)	0.897***
	(0.027)
UNEMPLOYMENT	−0.341***
	(0.125)
DGS10	−0.223
	(0.183)
Constant	5.244***
	(1.344)
Observations	227
R^2	0.826
Adjusted R^2	0.824
Residual Std. Error	3.808 (df = 223)
F Statistic	354.056*** (df = 3; 223)
Note:	*p<0.1; **p<0.05; ***p<0.01

When having VXO as the dependent variable, the story is different; only $DGS10$ is still not significant, but the results seem better than before; also, the R^2 is pretty high, at about 82%.

We can try to cut the sample in June 2008, similarly to how we did it before, and the result can be seen in Table 7.

Table 7: *Regression from 1991 to June 2008*

	Dependent variable:
	VXO
Lag(VXO, 1)	0.886^{***}
	(0.039)
UNEMPLOYMENT	-0.476^{**}
	(0.227)
DGS10	-0.048
	(0.166)
Constant	5.066^{***}
	(1.456)
Observations	209
R^2	0.832
Adjusted R^2	0.830
Residual Std. Error	2.954 (df = 205)
F Statistic	339.174^{***} (df = 3; 205)
Note:	*p<0.1; **p<0.05; ***p<0.01

This operation didn't make the regression perfect, but the standard error is better now than how it was before. However, we can still say nothing about the effects of Systematic Monetary Policy on the VXO index.

3.4 Why isn't the coefficient significant?

So far none of our sub-samples could produce a significant regression; one possible explanation can be found by examining more closely the time frame of our regression, and how systematic Monetary Policy shifted in that time frame. We can do that by looking at the time series of the Federal Funds Rate variable, the policy rate directly set by the Fed in FOMC meetings, and used as one of the primary tools of Monetary Policy. Basically, it's the interest rate at which banks in the US borrow money from each other overnight; in fact, it is often referred to as the *overnight interest rate*.

As we previously mentioned, this interest rate is set by the Fed in FOMC meetings, but the banks have no written obligation to follow it strictly. Here's how it works in detail.

For each banking organization in the Fed system, the end-of-the-day balances in the bank's account, averaged over two-week reserve maintenance periods, are used to determine whether it meets its reserve requirements (the amount of money a bank is legally required to have as reserve in the Fed's account). If a bank expects to have end-of-the-day balances greater than what's required, it can lend the excess amount to an institution that anticipates a shortfall in its balances. The interest rate the lending bank can charge is the federal funds rate, or Fed funds rate.

The FOMC makes its decisions about rate adjustments, but it cannot force banks to charge the exact federal funds rate. Rather, it sets a target rate; the actual interest rate the bank will charge is determined through negotiations between the two banks. The weighted average of interest rates across all transactions of this type is known as the effective federal funds rate. This is the indicator we are going to look at, and we can see its trend in Figure 2.

It's easy to see how from 2004 onward there is a big spike in the so-called "FEDFUNDS" rate, which could be the reason why the coefficient for the variable is not significant when we include this time period. In fact, some economists claim that this specific period in US monetary policy is particular, as it marked a significant deviation from Taylor's Rule predicted value.

The Taylor Rule is a rule for systematic monetary policy, which is formalized as follows:

$$i = \overline{r} + \pi + h(\pi - \pi^*) + b(y - \overline{y}), \quad h > 0,\ b > 0$$

where h is the relative weight given by the CB to deviations from the inflation

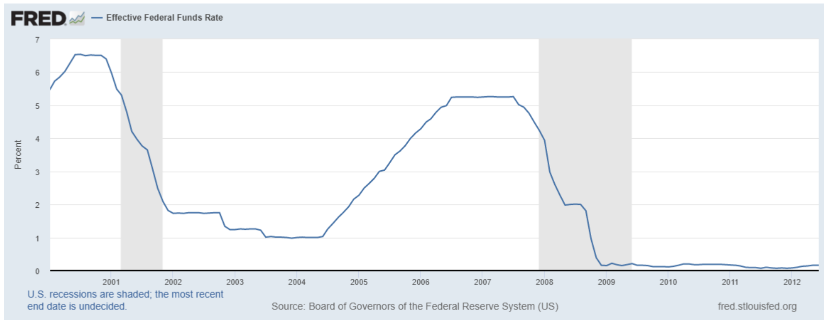


Figure 4: *In the graph we can see the trend of Effective Federal Funds Rate from 2000 to 2012; we can clearly see a period of low interest rates between 2002 and 2003, followed by a big spike from 2004 up until 2006*

objective, and b is instead the relative weight given by the CB to fluctuations in the level of output.

The policy prescription is as follows: if inflation goes up by 1%, the nominal interest rate reacts by $(1 + h)$, therefore more than 1%. This is the so-called Taylor Principle. The rationale is that if inflation is over the target, to lower it a CB may increase the nominal interest rate (so, in our case the federal funds rate) in order to increase the real interest rate, and thus lower inflation.

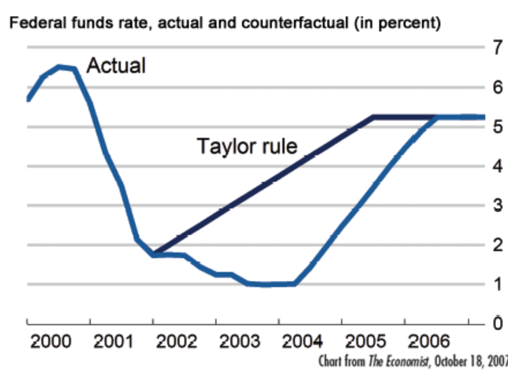


Figure 5: *Estimated deviation of US Monetary Policy from the counterfactual Taylor Rule, in the period between 2002 and 2006*

In Figure 3 we can see a graph of the deviation of US Monetary Policy from the Taylor Rule in this period, roughly from 2002 to 2005. We can easily see how much interest rates were kept low for too long, and then increased too quickly, when compared to the counterfactual Taylor Rule.

Thus what we could try to do is to use a sub-sample that goes from 1991 all the way to the end of 2002, and see if the coefficient for $DGS10$ is significant. When we do this, the result is as reported in Table 8.

Table 8: *New time frame: 1991-2002*

	Dependent variable:
	VXO
Lag(VXO, 1)	0.779^{***}
	(0.054)
UNEMPLOYMENT	-0.604^{**}
	(0.284)
DGS10	-0.927^{**}
	(0.372)
Constant	13.661^{***}
	(3.134)
Observations	143
R^2	0.837
Adjusted R^2	0.834
Residual Std. Error	2.961 (df = 139)
F Statistic	238.424^{***} (df = 3; 139)
Note:	*p<0.1; **p<0.05; ***p<0.01

As we can see, all coefficients are finally significant in this specific time frame; we can therefore make some observations about their signs. We can see for example that our $DGS10$ variable has a negative coefficient; this conclusion could be seen as puzzling, but in fact it can be explained easily.

In fact, the negative coefficient should not be seen as proof of a causal relationship between the easing of Monetary Policy (the lowering of the interest rate) and the level of financial uncertainty as captured by the VXO index; this would truly be an astonishing (and not so encouraging) result. Instead, we can find a more fitting explanation in the research from Caggiano, Castelnuovo and Nodari (see [3] for details).

In this paper the authors ask themselves if the Federal Reserve acts as a sort of risk-manager, responding to high level of financial uncertainty by modifying its policy decisions. To do this, they compute the "risk-management driven policy rate gap", measuring the difference between the actual policy rate and the counterfactual one (the rate it would have set in a world where uncertainty had not been present). The estimated median value of this policy rate gap is about 30 basis points, which is roughly equivalent to a standard policy rate move. However, in the presence of big spikes in economic uncertainty, such as in 1987 (Black Monday) and in 2008 (Great Recession), such a gap has been found to be three times as large. It is important to note that these results are found to be significant in spite of the presence of inflation, output gap, output growth, and two lags of the policy rate in the Taylor Rule used by the authors.

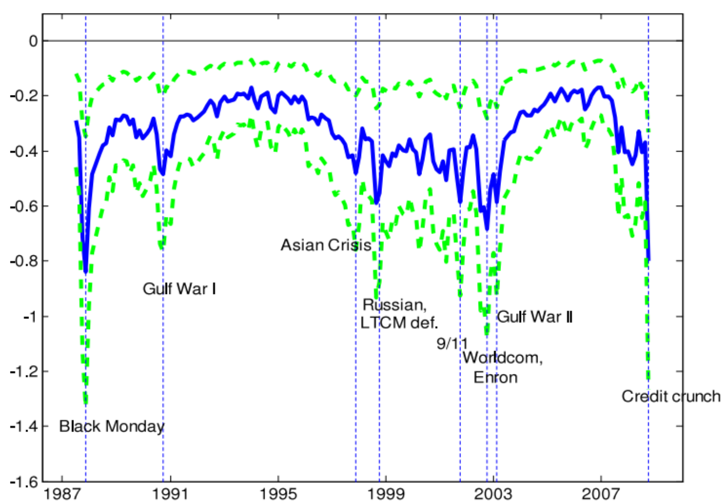


Figure 6: *Graph showing the time series for the risk-management driven policy rate gap, from 1987 until 2008. Green lines represent 90% confidence bands*

In the graph (which is borrowed from the paper) we can see how this policy rate gap is always significant, and always negative (at least in this time frame, which largely corresponds to the mandates of Alan Greenspan and Ben Bernanke as Chair of the Federal Reserve). This suggests a cautious approach of the Fed in the presence of economic uncertainty, resulting in an overall looser Monetary Policy when compared to the counterfactual one.

As an additional, final test, we can use directly the time series for the federal funds rate instead of $DGS10$, in order to assess more clearly the effects of systematic Monetary Policy on market volatility. Therefore we will have another regression, reported in Table 9 below.

Table 9: *Here we use the Federal Funds Rate instead of DGS10*

	Dependent variable:
	VXO
Lag(VXO, 1)	0.796^{***}
	(0.052)
UNEMPLOYMENT	-1.218^{***}
	(0.310)
FEDFUNDS	-0.516^{*}
	(0.302)
Constant	13.374^{***}
	(3.461)
Observations	143
R^2	0.833
Adjusted R^2	0.830
Residual Std. Error	2.997 (df = 139)
F Statistic	231.758^{***} (df = 3; 139)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Here we can see that all coefficients are significant, even if the coefficient for effective Fed funds rate is significant with only one degree of significance. Anyway, the coefficient is still negative, reinforcing our proposed explanation that Monetary Policy tends to be more expansionary during times of higher economic uncertainty.

On the other hand, unfortunately with the tools at our disposal and the results we got from our analysis we can't say anything more about how Monetary Policy itself impacts economic uncertainty; probably more research is needed to better assess this fundamental question about the effects of Monetary Policy decisions.

4 Summary and Conclusion

We started this work by asking ourselves a fundamental question: Does Monetary Policy Matter for Economic Uncertainty? We began by testing if Monetary Policy shocks in the US had some significant effect on the fluctuations in Economic Uncertainty, but we didn't find any compelling evidence of that, even when studying fluctuations in financial volatility with the VXO index.

Therefore, we went on to assess whether systematic Monetary Policy could better explain the behaviour of Economic Uncertainty proxies. We found no such proof when testing this hypothesis on the EPU index, but results on the VXO index were much more encouraging, and by reducing the time frame to the period from 1991 to 2002, we found evidence for a negative correlation between the level of interest rates and the level of Uncertainty in the economy (in particular, financial volatility).

This result, as we have stated before, could be seen as puzzling and unforeseen, as it seems to indicate that expansionary monetary policy inflates the level of uncertainty. However, we found a much more compelling explanation in the fact that the Fed, acting as a risk-manager, chooses a more expansionary Monetary Policy when Uncertainty is on the rise, thus creating the negative link we found. However compelling, this explanation does not provide us with any answer to our original question. We can't say anything for sure about the impact of Monetary Policy on Uncertainty. Probably Monetary Policy can be an useful tool to smooth spikes in the level of Uncertainty, especially in the time frames in which Monetary Policy is systematic and easily predictable. Maybe other types of policy, like Fiscal Policy (specifically announcements concerning future fiscal plans), can then be charged with the task of reducing overall Economic Uncertainty.

Anyway, probably the tools at our disposal, or the time frame taken into examination, could not provide us any more insights into this matter, reinforcing the belief that much more research on the matter of Monetary Policy and its effects on Uncertainty is needed to untangle this question.

Therefore, I would like to end this work with some fitting lines from Nicholas Bloom's paper *Fluctuations in Uncertainty*, who could sum up perfectly the conclusion to our analysis:

> *"While the empirical progress on fluctuations in uncertainty over the last decade has been exciting, there is still much about uncertainty about which we remain uncertain."*

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