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Risk Aversion vs Ambiguity Aversion: what do data tell us?

An empirical analysis of the macroeconomic effect of VIX and EPU

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1 Introduction

In the last years, part of the economic literature focused on the role of uncertainty in the real economy, mainly trying to understand the effect that uncertainty has on the business cycle. However, the economic research has focused on a vague concept of "uncertainty", without actually taking into account all its dimensions. In fact, it has been showed that there is a fundamental difference between the so-called *risk* and *ambiguity*. Due to the difficulty in empirically differentiating between these two dimensions, structural models in the economic literature have commonly made use of general proxies for uncertainty, even if economists are aware of the fact that the broad concept of uncertainty incorporates various nuances. In fact, several authors investigate the effect of "uncertainty" without differentiating between risk and ambiguity (e.g. Moore, 2017).

Each different dimension of uncertainty might have a different effect on investors' decision-making process, thus on the real economy. In fact, all economic models include agents making decisions: if the assumptions on the decision-making process are not complete, the model might not be informative of the real world. The importance of empirically investigating the different dimensions of uncertainty derives from the necessity of calibrating structural models with proxies that are the most representative as possible of the real world.

Two well-known proxies for uncertainty used in the economic literature are the VIX and EPU indexes. After their decoupling in mid-2010 concerns about these measures have been raised: are VIX and EPU measuring the same type of uncertainty? The purpose of this work is to investigate the relationship between these two measures, their effect on the real economy and whether they can be distinguished between measures of risk aversion and ambiguity aversion. In particular, the work analyses the effect of uncertainty shocks of VIX and EPU on Industrial Production, Un-

employment Rate and Consumer Credit in the US from January 1990 to February 2019.

Several studies investigate the relationship between VIX and EPU (e.g. Deutsche Bank Research, 2018 and Shaikh, 2019). Moreover, some authors also tried to explain the puzzle investigated in this work of the decoupling between VIX and EPU (e.g. Pastor and Veronesi, 2017; European Central Bank, 2017 and Tiwari, Jana, and Roubaud, 2018). However, none of them tries to explain the differences between these two indexes through the concept of ambiguity aversion. The originality of this work derives from the introduction of the concept of ambiguity and ambiguity aversion as an explanation for the decoupling of these two measures.

The work is structured as follows: this section introduces the concept of uncertainty and explains the relationship between VIX and EPU, including their decoupling. Section 2 describes the data and the statistical methodology used in the empirical analysis. Section 3 estimates different VAR models in order to investigate the macroeconomic effect of VIX and EPU. Section 4 summarizes the results and concludes.

1.1 Uncertainty: the difference between risk and ambiguity

Uncertainty has always been an amorphous concept in the economic literature, often leading to confusion and misinterpretation. The interest in this concept picked after the Great Recession when economists tried to explain the role played by uncertainty. Uncertainty has been proven to have an effect on the real economy, therefore it is crucial to understand how economic agents behave in uncertain situations so that economic models can reflect the real behaviour of economic actors and policymakers can make informed decisions. We commonly refer to uncertainty when speaking about a situation with a lack of certainty about the future outcome. However, in

behavioural economics, this concept has different important nuances that might represent different economic implications and must be taken into account to understand how economic actors behave in situations of uncertainty.

The first important contribution in understanding this concept comes from Knight (1921), who for the first time differentiated between risk and uncertainty. According to Knight, risk is "measurable uncertainty", meaning that economic actors know all the possible outcomes of an uncertain situation and they can assign a numerical probability to each outcome. On the other hand, uncertainty is unmeasurable, meaning that the set of all possible outcomes and/or the probability distribution of all possible outcomes is unknown for the economic actors. Therefore, according to Knight, measurable risk can be eliminated through the insurance markets, whereas unmeasurable uncertainty cannot be eliminated.

Following this work, the so-called *subjective probability theory* was developed, with Savage (1954) and Ramsey (1926) as two of the main exponents. This theory argues that even in the case of "unmeasurable uncertainty", economic agents develop some "degree of belief" (Ramsey, 1926), creating some sort of subjective probabilities of all possible outcomes based on personal judgment so that they behave as if they assigned numerical probabilities following the mathematical rules of probabilities. Numerical probabilities can be inferred from actual choices of agents, that by acting (e.g. placing a bet on one event) show their subjective (numerical) probability distribution of events. According to this part of the literature, there is no fundamental difference in how agents behave in situations of risk or uncertainty.

Building on this growing interest in the concept of uncertainty in the behavioural economic literature, Ellsberg's seminal article (1961) highlighted the difference between measurable and unmeasurable uncertainty, introducing the concept of ambi-

guity and ambiguity aversion. One of the most cited contributions by Ellsberg is the so-called Two-Urns Ellsberg Paradox (Ellsberg, 1961, p.650-651). In this famous experiment, individuals were asked to choose between four bets involving randomly drawing a ball from two urns containing both 100 red and black balls. The first urn had an unknown distribution of the colours and the second urn had a known split of 50/50 between red and black balls. Individuals were asked to rank the following four bets:

- B1: betting on drawing from the first urn and betting on red
- B2: betting on drawing from the second urn and betting on red
- B3: betting on drawing from the first urn and betting on black
- B4: betting on drawing from the second urn and betting on black

The behaviour shown on average by individuals was of indifference between B1 and B3, and between B2 and B4. However, they preferred to bet on the second urn rather than the first one, that is they preferred to bet over the known probability distribution of red and black balls rather than unknown probability distribution of the two colours.

These results were paradoxical at the time because they contradicted the subjective probability theory. In fact, if one wanted to infer numerical probabilities from the actions of the economic agents, they would face the following paradox: B1 $<$ B2 implies that the subjective probability of drawing a red ball in the first urn is less than $\frac{1}{2}$ (since the probability of drawing a red ball in the second urn – i.e. B2 – is known and it is equal to $\frac{1}{2}$). At the same time and for the same reasons, B3 $<$ B4 implies that the probability of drawing a black ball in the first urn is less than $\frac{1}{2}$. The paradox relies on the fact that, inferring subjective probabilities from these results, the probability of drawing a red ball and a black ball from the first urn would not add up to 1, leading to a non-rational result.

Ellsberg (1961) commented on this paradox claiming that there are situations in which it is impossible to infer numerical probabilities from actual choices and that this is due to the existence of a type of uncertainty that cannot be reduced to risk and that is perceived by economic agents in a different way. The conclusion that can be drawn from these paradoxes is that economic agents prefer to bet on something where the probability distribution is known rather than on something where the probability distribution is unknown. Therefore, he explained this paradox by developing the concept of ambiguity aversion, according to which economic agents try to escape from situations in which information is ambiguous, i.e. not reliable, not credible, not adequate and/or conflicting. Ellsberg himself described this concept as "[...] ambiguity of information, a quality depending on the amount, type, reliability and "unanimity" of information, and giving rise to one's degree of "confidence" in an estimate of relative likelihoods."(Ellsberg, 1961, p. 657). The situation faced by economic agents in ambiguous scenarios cannot be classified either as complete ignorance, as the agents have information about the situation, nor as risk, as they cannot use this information to form some sort of numerical probabilities.

1.2 Measuring uncertainty

As explained in Section 1.1, the concept of uncertainty itself is amorphous, so it is not surprising that measuring it is always complicated. Several different measures or indicators of uncertainty have been developed in the past years by researchers, and they can be classified into three major groups (Bontempi, Golinelli, Squadrani, 2016):

- The "finance-based" measures are based on the stock market volatility, taken as an indicator of investors' uncertainty about the future. These measures are representative of the uncertainty perceived by investors, that is a restricted group of economic agents. A very commonly used example is the VIX index,

that will be described in detail in Section 2.1.

- The "forecasts-based" measures are based on the idea that the uncertainty is basically represented by the difficulty of forecasting the future. Therefore, they measure the divergence between several different professional forecasts as a proxy of the difficulty to predict the future, i.e. uncertainty.

- The "news-based" measures assume that the media are the instrument through which uncertainty is perceived by the general public, meaning that a high frequency of news regarding a specific matter measures how much the general public is worried about that matter. Part of these measures focus on the media, that is they count the frequency of publication of newspaper articles with certain words that remind to uncertainty. A well-known index in this category is the EPU index, that measures newspaper articles related to economic policy uncertainty as a proxy for it (a detailed description of the EPU index is provided in Section 2.1). Another part of this group of measures focuses on the receiver of the information, measuring the frequency of internet searches done by individuals of specific words. The key assumption of these measures is that high interest in certain topics from the general public actually reveals their uncertainty about those specific topics. In recent literature, measures based on searches of both macro-related and non-macro-related topics have been developed (Donadelli, 2014; Donadelli and Gerotto, 2019).

The fact that all these measures of uncertainty have been developed clearly manifest the absence of an objective way of measuring uncertainty. It must be remembered that uncertainty is an unobservable phenomenon and therefore the use of a proxy in economic models is required. However, assessing the adequacy of a proxy is always difficult and it might be that some proxies are not really capturing the phenomenon that we want to analyse or they might be noisy, meaning that they

are not capturing only that phenomenon. Usually, in research, one way of judging a new measure of uncertainty is to look at the correlation with other well-known and used measures. In fact, it can be observed that all the major measures of uncertainty have a relatively high correlation, that is they tend to move together (Forbes, 2016). Since this high correlation between one and another, in structural models these measures are often used interchangeably, as they are seen as different measures for the same phenomenon. However, there is a lot of uncertainty about what each indicator is actually capturing. It has been shown that the correlation of different measures of uncertainty with different macroeconomic variables varies depending on the measure chosen (Forbes, 2016). This means that these several measures that are used interchangeably in structural models might capture different aspects of uncertainty and have a different effect on the real economy. This result justifies the interest in investigating what these indicators are actually capturing. In particular, this work focuses on investigating if VIX and EPU are measures of risk aversion and ambiguity aversion respectively.

1.3 VIX and EPU: are they measuring the same thing?

As seen in Section 1.2, there is a lot of uncertainty around what each uncertainty measures actually captures. Two well-known and often interchangeably used measures of uncertainty are the VIX and EPU indexes. On the one hand, the VIX index is the 30-day volatility implied in the S&P500 options prices and it is often referred to as the "fear index", as it measures the level of portfolio protection in the financial market ("Wall Street"). On the other hand, the EPU index is a news-based measure of economic policy uncertainty, that is the uncertainty about fiscal matters, government spending and general elections as examples. It is considered as an indicator of political uncertainty perceived by the general public ("Main Street"). Please refer to Section 2.1 for a detailed explanation of the variables.

The rationale behind their interchangeable use in structural models is the fact that they usually display a high level of correlation. In fact, as can be observed in Figure 1, these two measures tend to co-move, showing a correlation of 42% over the period from January 1990 and February 2019.

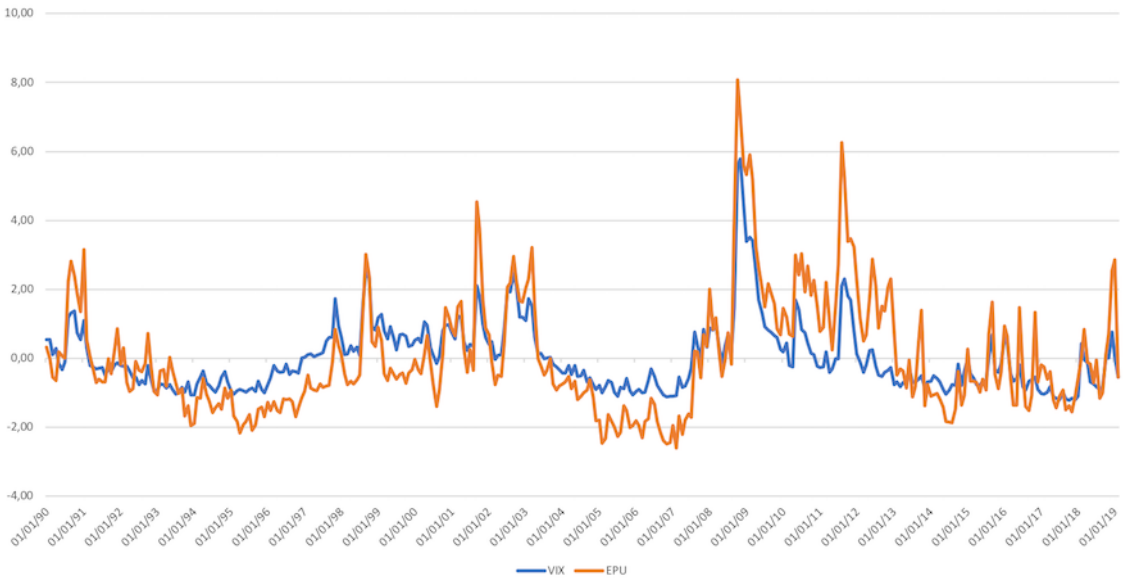

Figure 1: Monthly observations of VIX and EPU, in standardised terms, from January 1990 to February 2019

However, from 2010 on, the correlation between these two measures diminished drastically in specific periods. The phenomenon of two variables losing their previously high correlation is called *decoupling*. Figure 2 clearly shows three periods after 2010 in which VIX and EPU decoupled. The first period coincides with the period immediately before the debt ceiling crisis in mid-2011, in which the correlation between VIX and EPU was -13%. The second and third periods coincide with the period immediately before the fiscal cliff in January 2013 and the period immediately after Trump's election in November 2016, with a correlation of the two measures of 6%. All these periods have in common a high economic policy uncertainty combined with low market volatility, meaning that economic policy uncertainty (measured by the EPU) seems not to be translated into market volatility (measured by the VIX).

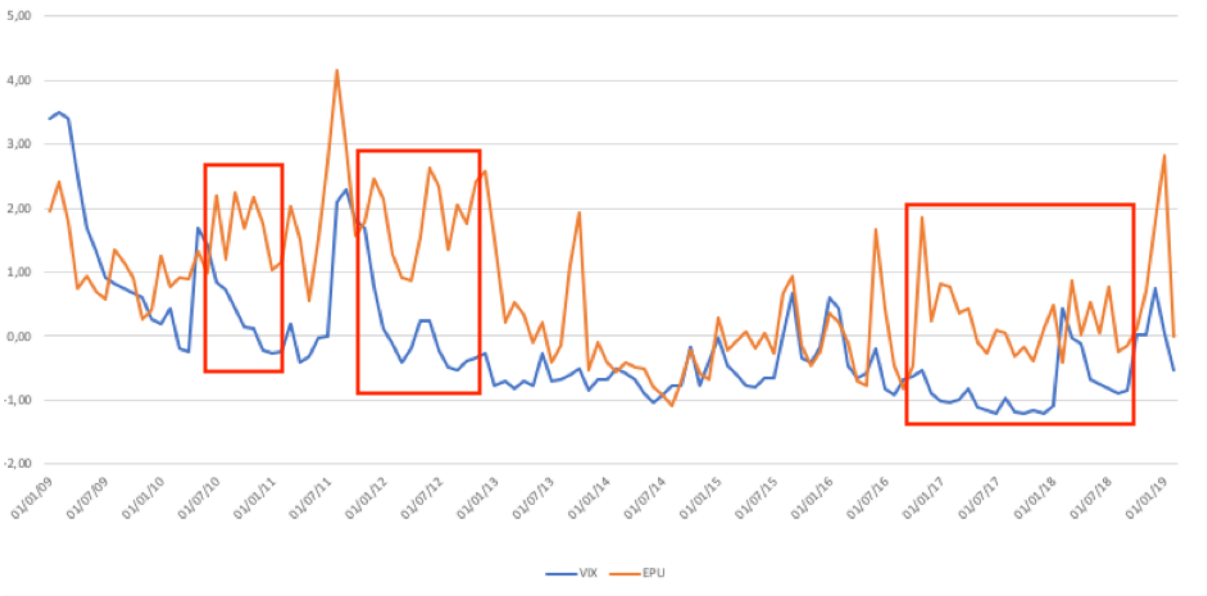

Figure 2: Monthly observations of VIX and EPU, in standardised terms, from January 2009 to February 2019. Red lines indicate the periods of decoupling of the two variables

These periods of decoupling are actually puzzling for the economic theory. In fact, we would usually expect financial markets to respond to high levels of economic policy uncertainty with a high level of expected volatility and portfolio protection. It is perfectly intuitive that, in periods of uncertainty around economic policy, investors would express their fear by hedging their positions and insuring their portfolios, making the level of VIX raise. Pastor and Veronesi (2013) developed a model in which they show how financial markets respond to news related to economic policy. In their contribution, they introduce a *political risk premium* that investors require in situations of political uncertainty. According to their intuition, the uncertainty that arises from policy-related matters should determine a risk premium and increase stock market volatility. In light of this theoretical interpretation, it is clear why the decoupling between VIX and EPU is puzzling: are investors behaving irrationally, underestimating the risk coming from political news? Why is Wall Street not worried about the political uncertainty that affects Main Street?

In a later contribution, Pastor and Veronesi (2017) try to explain the decoupling

between these two measures by highlighting the concept of "precision of political signals". In their article, they argue that market volatility is a function of political uncertainty, but also of the precision of political signals, that is how informative news is about the future action of the government. The key focus of this argument is how investors get the information that will form their expectations about the future. The idea is that news about economic policy is the way through which investors learn about future's government actions and they incorporate this information into their decision-making process. When the precision of the political signals is high, investors are able to update their beliefs about the future government's action and act in accordance. However, when the precision of political signals is low, investors are not able to extract precise and useful information from the news, resulting in a small update in their beliefs and therefore low market volatility. According to this interpretation, investors are not behaving irrationally, but, on the contrary, they are rationally responding to the low precision of political signals.

Building on the contribution by Pastor and Veronesi (2013, 2017), this work argues that what investors are responding to is the *ambiguity* of the information received. In fact, recalling the definition given by Ellsberg (1961), ambiguity is a quality of information of not being credible, reliable, meaning that even in the presence of a high amount of information the economic agents cannot incorporate it into their decision-making process as they cannot understand it or they do not trust its truthfulness. Ambiguity of information affects investors' decision by placing more weight on the worst-case scenario (Epstein and Schneider, 2008), and by lowering financial market participation (Antoniou, Harris, and Zhang, 2015). Indeed, in presence of ambiguity, investors prefer not to hold risky assets as they cannot use the information received to form a probability distribution of future outcomes, exactly what happened to the participants of the Two-Urns experiment by Ellsberg (1961) when they preferred not to bet on the urn with unknown probability distribution

of red and black balls. This results in low market volatility coupled with high economic policy uncertainty. In fact, when analysing the periods in which VIX and EPU decoupled – the period immediately before the debt ceiling crisis in 2011, the period immediately before the fiscal cliff in January 2013 and the period immediately after Trump's election in November 2016 – they coincide with periods of possibly high ambiguity of information.

Moreover, recalling the distinction made by Knight (1921), risk can be eliminated through the insurance market whereas uncertainty (in particular ambiguity) cannot. When EPU is high and VIX is high it means that investors are insuring their portfolios, eliminating the risk that arises from economic policy. On the contrary, when EPU is high but VIX is low, investors are not protecting their portfolios because the uncertainty that they are facing is not in the form of risk, but ambiguity, therefore not eliminable through insurance.

The main argument of this work is that investors are not irrational, but they rationally respond to a specific nuance of the concept of uncertainty: ambiguity. In periods characterised by ambiguity of information, the VIX index is low because investors are confused (political signals are difficult to interpret) and they cannot form a probability distribution of future outcomes. The idea is that when EPU is high and VIX is low there might be some ambiguity in the market and the ambiguity aversion of economic actors might be captured by the EPU index since higher frequency in articles related to economic policy might also be a measure of the perceived ambiguity of the general public.

This work investigates whether the EPU index captures some sort of ambiguity aversion by comparing its effect on the real economy with the effect of the VIX index. The idea is to compare the effect that these two measures have on some

macroeconomic indicators to see if there is a difference. The study is carried out on the effect that these two measures have on the real economy because this is what really matters when calibrating a structural model. In fact, this work focuses on the use that has been done in the past literature of these two indexes: both have been used interchangeably as measures of uncertainty, but they might capture different nuances of the concept of uncertainty and different behaviours of economic agents, and the decoupling offers the opportunity to further investigate the differences in these two measures.

2 Data description and methodology

This chapter describes the variables used in this work and briefly explains the VAR model, used for the empirical analysis.

2.1 Measures of risk aversion and ambiguity aversion: VIX and EPU

As explained in Section 1.3, the VIX and EPU indexes are both measures used as a proxy for general uncertainty. However, they are conceptually different and they might capture different aspects of the so-called uncertainty, i.e. risk and ambiguity.

The Implied Volatility Index (VIX) was introduced in 1993 by the Chicago Board Options Exchange (CBOE). It measures the 30-day volatility implied in the price of the S&P500 index at-the-money options and, for this reason, it falls into the category of "finance-based" measures of uncertainty. Indeed, it is a measure of the market expectations about future volatility for the following 30 days and it is often referred to as the "fear index". Based on the way it is built, one could argue that the VIX is a pure measure of expected volatility, capturing not only the fear of decreasing prices but also the opportunity of increasing ones. However, the S&P500 option market is actively used for insurance purposes. In fact, investors that are concerned about a possible future drop in the stock market will probably hedge their position by buying S&P500 put options, that is acquiring the right to sell the S&P500 at a future date at a fixed price. The more investors are worried about a drop in future stock prices, the more the volume and the price of S&P500 put options will increase, and the more the VIX index will increase. For this reason, the VIX index is considered a measure of investors' fear, as it measures the price of portfolio protection (Whaley, 2009). Moreover, the response of VIX index to movements in the S&P500 index has been proven to be asymmetrical, meaning that

the rise in VIX due to a unit drop in the S&P500 is greater than the decrease in VIX due to a unit increase in the S&P500 (Whaley, 2009). These results further confirm and reflect the fact that the S&P500 option market is mainly used by investors for hedging strategies. For the purpose of this work, the VIX index has been chosen as a measure of risk aversion because it captures investors' reluctance to a type of uncertainty that is measurable and that can be eliminated through the insurance market, the exact definition of risk according to Knight (see Section 1.1). Monthly data from January 1990 to February 2019 about the VIX index have been retrieved from the Federal Reserve Bank of St. Louis database (FRED).

The Economic Policy Uncertainty (EPU) index was created by Baker, Bloom and Davis (2015) to study the effect that economic policy uncertainty might have on the real economy and the business cycle. The EPU index is composed of three components. The first component is an index based on the frequency of published articles in 10 leading US newspapers referring in some way to uncertainty regarding economic policy. The articles in question must contain particular words related to three main categories: economy (E), policy (P) and uncertainty (U). For example, for the first category, one word could be "uncertain" or "uncertainty", for the second category "economic" or "economy", and for the third "congress", "regulation" "white house", "legislation", "deficit" or "federal reserve". The second component is an indicator of the amount of federal tax code provisions that will expire in the next 10 years, measuring the uncertainty surrounding the future federal tax code. The third component measures the uncertainty related to some policy-related macroeconomic variables, such as Federal expenditure or Consumer Price Index, by using the disagreement among researchers as a proxy. The EPU index is an example of "news-based" measure of uncertainty and this work investigate the possibility of it capturing ambiguity aversion due to the fact that, measuring the frequency of newspaper articles, it might also capture other characteristics of news, such as be-

ing ambiguous in certain periods. Monthly data from January 1990 to February 2019 about the EPU index have been retrieved from the Federal Reserve Bank of St. Louis database (FRED).

2.2 Macroeconomic measures: Industrial Production, Unemployment Rate and Consumer Credit

In order to understand the effect of shocks in VIX and EPU on the real economy, the following three US macroeconomic variables have been chosen: Industrial Production index (IP), the Unemployment Rate (UR) and the Consumer Credit (CC). The Industrial Production index is a measure of the real output of the following industries in the US: manufacturing, mining, electric and gas utilities. The Unemployment Rate measures the number of people aged 16 or older, resident in the US, and who are not in institutions such as penal or mental facilities, that are unemployed as a percentage of the total labour force. Consumer Credit (owned and securitized) represents the credit extended to consumers in the US. These variables have been included in the analysis as macroeconomic indicators representative of the US real economy. Monthly data from January 1990 to February 2019 about all three variables have been retrieved from the Federal Reserve Bank of St. Louis database (FRED).

2.3 Vector Autoregressive (VAR) Model

The vector autoregressive (VAR) model is a well-known model used to understand the dynamic relationship between different variables. The VAR model is an extension of the univariate autoregressive model to the multivariate form. In fact, it is an autoregressive model where the elements are not single variables but vectors of multiple variables. Each variable included in the system is regressed on p lags of itself and on p lags of all the other variables in the model, giving rise to a system of

multiple regressions. For this reason, an optimal number of lags should be selected with the help of the information criteria of Akaike (AIC), Schwarz Bayesian (BIC) and Hannan-Quinn (HQC). The VAR methodology is commonly used in structural analysis as it helps to explain the dynamic behaviour of different variables over time (Zivot and Wang, 2006).

The VAR(p) model can be written as follows:

$$\mathbf{Y_t} = \mathbf{c} + \mathbf{B_1}\mathbf{Y_{(t-1)}} + \mathbf{B_2}\mathbf{Y_{(t-2)}} + \cdots + \mathbf{B_p}\mathbf{Y_{(t-p)}} + \boldsymbol{\varepsilon_t}; \quad \textit{with} \quad t = 1, \ldots, T$$

Where:

- $\mathbf{Y_t}$ is a $(N \times 1)$ vector composed by time-series variables;
- $\mathbf{c}$ is a vector of constants;
- $\mathbf{B_i}$ are $(N \times N)$ coefficient matrices;
- $\boldsymbol{\varepsilon_t}$ is the vector of with noise error terms.

The VAR model is sensitive to how the variables are ordered. In fact, the ordering of the variables imposes a recursive structure, meaning that in the vector $\mathbf{Y_t} = [y_1, y_2, y_3, y_4]'$ the variable y_2 has a contemporaneous effect on the variables on its right (y_3 and y_4), and a lagged effect on the variables on its left (y_1). For this reason, the ordering is crucial in a VAR model and should be justified by theory and results should always be checked for robustness.

In structural analysis, in order to understand and interpret the VAR analysis, two important instruments are used: the Impulse Response Functions (IRFs) and the Forecast Error Variance Decomposition (FEVD).

The Impulse Response Function (IRF) is one of the most used instrument to interpret the VAR model as it explains the dynamic response of a variable to a one-time shock in another endogenous variable. With the term "shock" we commonly refer to an unexpected increase in a variable. In this analysis, the effect of one standard deviation shocks is investigated, meaning that the quantum of the unexpected increase is one standard deviation with respect to the mean of the variable under analysis. IRFs are usually shown through a plot that includes confidence bands to assess the statistical significance of the results. IRFs are used in this work to evaluate the effect of a shock in VIX or EPU on the US real economy, represented by the three macroeconomic indicators chosen.

Another important instrument used to interpret the dynamic behaviour of variables included in a VAR model is the Forecast Error Variance Decomposition. A shock in a variable not only has an effect on the variable itself, but the shock is dynamically transferred to all the other variables in the model. The Forecast Error Variance Decomposition shows the portion of the forecast error variance of a variable at a certain time horizon that can be explained by the shock in the other variables (Brooks, 2014). In other words, it helps understand how much the shock in a variable (e.g. VIX or EPU) affects the variance of the other variables (e.g. the macroeconomic indicators included in the VAR).

It is worth noting that these two instruments are consistent estimators even in the presence of non-stationary variables. In fact, according to Phillips (1998), the impulse response functions and the forecast error variance decomposition are inconsistent with non-stationary variables only at long horizons. Indeed, this methodology has been used to study uncertainty shocks in several influential works (e.g. Bloom, 2009 and Alexopoulos and Cohen, 2009).

3 Empirical Analysis

In this chapter, the empirical analysis is carried out by estimating the VAR models and evaluating the response of the chosen macroeconomic indicators to a shock in either VIX or EPU. First of all, two baseline VARs are estimated: both have all the macroeconomic variables, but one is with the VIX as a measure of risk aversion and the other with EPU as a measure of ambiguity aversion. Then, a var with both measures is estimated to study the dynamic behaviour of the variables when both measures are in the system. The analysis continues by studying two sub-samples: before and after the decoupling of VIX and EPU happened in mid-2010. The chapter ends with a battery of robustness checks.

3.1 VAR with VIX IP UR and CC

The first estimated VAR is the following $\mathbf{Y_t} = [VIX, IP, UR, CC]'$. For this VAR, the AIC criterion indicates 4 as optimal lags, the BIC criterion 1 lag and the HQC criterion 2 lags. Therefore, for the sake of robustness, the model and the relative impulse response functions have been estimated with 1, 2 and 4 lags separately. The VIX index has been ordered first, in line with Bloom (2009), reflecting the assumption that it has a contemporaneous effect on the macroeconomic variables. The impulse response functions of the three macroeconomic variables to a shock in VIX are presented in Figure 3.

The specification of the models related to the number of lags chosen do not consistently influence the results, that are very similar for all three estimated models. A standard deviation shock in VIX results in a long-lasting drop in industrial production of approximately 0.006 percentage points (pp), confirming that the VIX index is countercyclical. The response of the unemployment rate to a one standard deviation shock in VIX is a long-lasting increase of around 0.03 pp, due to the delayed

investment and hiring decisions induced by uncertainty. At the same time, consumer credit negatively responds to a shock in VIX due to raising borrowing cost caused by high uncertainty on the supply-side and the increase in precautionary savings (and decrease in borrowing) on the demand-side.

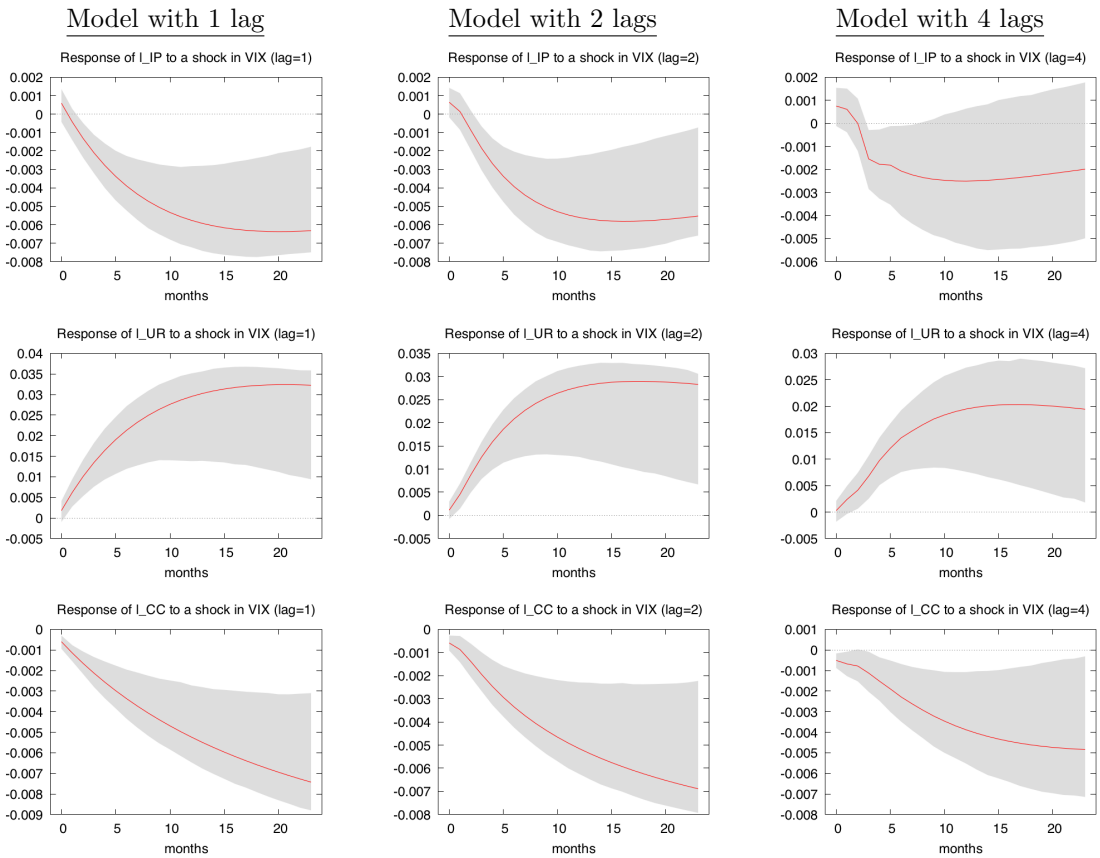

Figure 3: Impulse Response Functions of the macroeconomic variables to a shock in VIX. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in VIX. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

Table 1 shows the forecast error variance decomposition of the three macroeconomic indicators. In particular, it shows the percentage of the variability of the macroeconomic variables can be explained by a shock in VIX. After 24 months, a standard deviation shock in VIX explains around 28.9 percent of industrial production variability, 49.9 percent of unemployment rate variability and 36.8 percent of consumer

credit variability. These results suggest that a shock in VIX accounts for a consistent proportion of the variability of the three macroeconomic variables.

Table 1: Forecast Error Variance Decomposition of IP, UR and CC with respect to a shock in VIX

Horizon (months)	Industrial Production	Unemployment Rate	Consumer Credit
1	1.3	0.22	1.6
6	7.7	20.6	10.5
12	20.1	38.6	23.8
18	26.1	46.1	32
24	28.9	49.9	36.8

Note: Table shows the proportion (percentage) of forecast error variance of Industrial Production, Unemployment Rate and Consumer Credit that can be explained by a standard deviation shock in VIX after 1, 6, 12, 18 and 24 months. The model has been estimated with 2 lags.

3.2 VAR with EPU IP UR and CC

The second estimated VAR is the following $\mathbf{Y_t} = [EPU, IP, UR, CC]'$. As for the previous estimation, the VAR model and the relative impulse response functions have been estimated with 1, 2 and 4 lags separately in accordance with the information criteria. Again, the EPU index has been ordered first, reflecting the assumption that it has a contemporaneous effect on the macroeconomic variables. The impulse response functions of the three macroeconomic variables to a shock in EPU are presented in Figure 4.

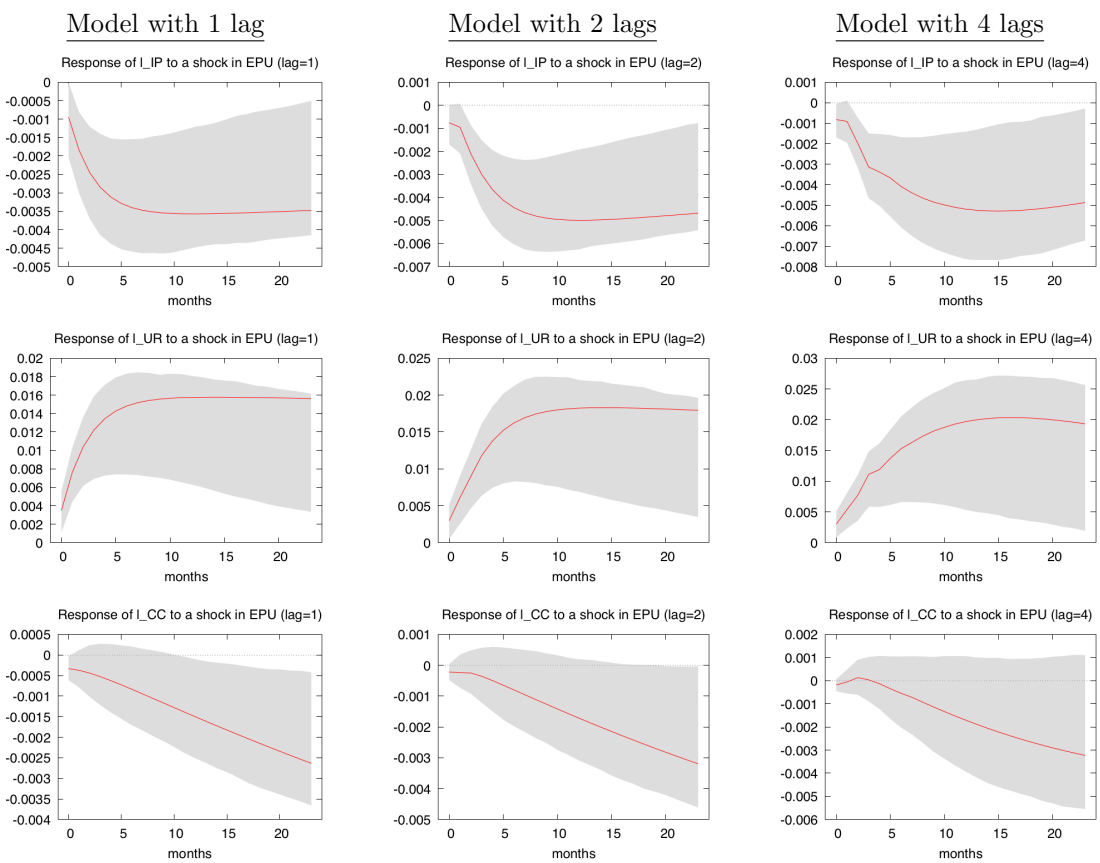

Figure 4: Impulse Response Functions of the macroeconomic variables to a shock in EPU. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

A standard deviation shock in EPU have very similar effects to a standard deviation

shock in VIX: industrial production drops by 0.005 pp, the unemployment rate respond with a long-lasting increase of around 0.018 pp and the effect on consumer credit is negative, although not statistically significant. The responses of the three macroeconomic indicators to a shock in EPU and VIX are very similar, thus leading to the conclusion that there is no substantial difference in the explanatory power of the two proxies. Both of them are countercyclical, depressing industrial production and consumer credit and increasing the unemployment rate.

When looking at the forecast variance decomposition (Table 2) the similarities between the two measures are confirmed. After 24 months, a standard deviation shock in EPU explains around 29 percent of industrial production variability and 30.1 percent of unemployment rate variability. This means that a shock in EPU explains the same proportion of the variability of industrial production and a slightly lower proportion of unemployment rate compared to the VIX. The only exception is the consumer credit: in fact, a shock in EPU accounts just for 7.2 percent of consumer credit variability, compared to 36.8 percent of the VIX (see Table 1). The difference in the explanatory power of VIX and EPU with respect to consumer credit could be due to the difference between risk and ambiguity. In fact, risk (measured by the VIX) is measurable and can be incorporated in higher credit spreads, making the cost of finance increase, and in turn, depressing the availability of credit. On the contrary, ambiguity (measured by the EPU) is unmeasurable and cannot be reflected in credit spreads, thus not affecting the consumer credit with the same channels as risk does. Without giving too much importance to this aspect with respect to the other macroeconomic indicators, it is reasonable to claim that there seems to be some evidence of the different explanatory ability of VIX and EPU with respect to consumer credit that could be linked to the difference between risk aversion and ambiguity aversion.

Table 2: Forecast Error Variance Decomposition of IP, UR and CC with respect to a shock in EPU

Horizon (months)	Industrial Production	Unemployment Rate	Consumer Credit
1	1.7	1.4	0.22
6	13.7	15	0.44
12	23.7	24.3	2
18	27.4	28.1	4.4
24	29	30.1	7.2

Note: Table shows the proportion (percentage) of forecast error variance of Industrial Production, Unemployment Rate and Consumer Credit that can be explained by a standard deviation shock in EPU after 1, 6, 12, 18 and 24 months. The model has been estimated with 2 lags.

3.3 VAR with VIX EPU IP UR and CC

In this section the following VAR is estimated $\mathbf{Y_t} = [VIX, EPU, IP, UR, CC]'$. The VIX index is included in a VAR together with the EPU index in order to see if the responses to a shock in EPU change controlling for the effect of VIX. The VIX has been ordered first to reflect the assumption that it has a contemporaneous effect on EPU and the macroeconomic variables. The model has been estimated with two lags. Figure 5 shows the impulse response functions of the three economic variables to a shock in EPU in a system where also the VIX is included.

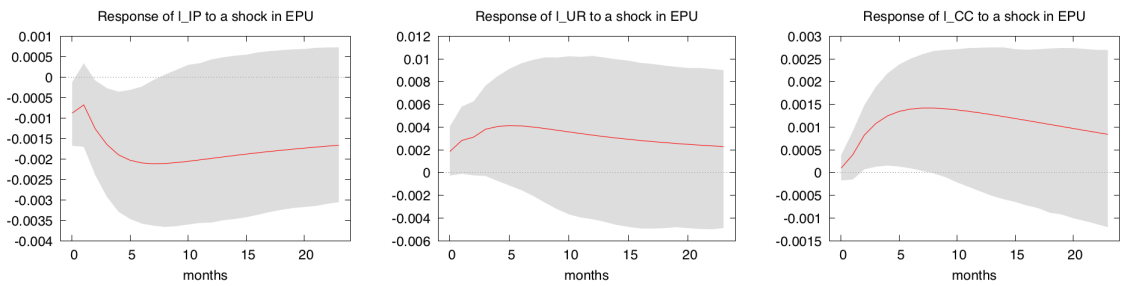

Figure 5: Impulse responses to a shock in EPU controlling for VIX. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU controlling for VIX. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

The responses of industrial production and unemployment rate to a standard deviation shock in EPU, although less pronounced and not statistically significant, do not differ so much from the one displayed by the baseline VAR with EPU and the macroeconomic indicators (see Figure 4). However, we note that the response of consumer credit to a shock in EPU, although not statistically significant, is now positive, as opposed to the negative response showed by the baseline VAR in Figure 4. When introducing VIX and EPU in the same model, the response of consumer credit to a shock in EPU differs from the one estimated in the baseline VAR and this could confirm the different channel through which VIX and EPU affect consumer credit, thus confirming their different explanatory ability with respect to this

macroeconomic indicator.

Table 3: Forecast Error Variance Decomposition of IP, UR and CC with respect to VIX and EPU including both in the model

VIX ordered first						
Horizon (months)	Industrial Production		Unemployment Rate		Consumer Credit	
	VIX	EPU	VIX	EPU	VIX	EPU
1	1	2.4	0.2	0.6	1.5	0.05
6	8.1	4.4	20.8	1.7	10.2	2.7
12	20.4	4.8	38.6	1.3	23.5	3.2
18	26.2	4.4	46.2	1	31.8	2.5
24	29	4.1	50	0.9	36.8	2
EPU ordered first						
Horizon (months)	Industrial Production		Unemployment Rate		Consumer Credit	
	VIX	EPU	VIX	EPU	VIX	EPU
1	2.3	1.2	0.03	0.8	1.5	0.06
6	4	8.5	14.5	8	12.8	0.2
12	12	13.1	29.2	10.8	26.5	0.2
18	16.5	14.2	36	11.3	33.7	0.6
24	18.6	14.4	11.4	39.5	37.5	1.3

Note: Table shows the proportion (percentage) of forecast error variance of Industrial Production, Unemployment Rate and Consumer Credit that can be explained by a standard deviation shock in VIX or EPU after 1, 6, 12, 18 and 24 months, differentiating between the ordering of the two indexes. The model has been estimated with 2 lags.

The forecast error variance decomposition in Table 3 shows that, when VIX is included in the model and it is ordered first, it captures all the variability of the macroeconomic indicators. In fact, after 24 months, a standard deviation shock in VIX accounts for 29 percent of the variability of industrial production (vs 4.1% of EPU), 50 percent of the variability of unemployment rate (vs 0.9% of EPU) and 36.8 percent of the variability of consumer credit (vs 2% of EPU). A shock in VIX is responsible for all the variability of the macroeconomic indicators when it is in a system with EPU, leading to the conclusion that the explanatory power of EPU does not differ from the one of VIX. However, when looking at the forecast error variance decomposition of the VAR in which EPU is ordered first, the proportion of variability related to a shock in EPU increases to 14.4 percent for industrial produc-

tion (vs 18.6% of VIX), and to 39.5 percent for the unemployment rate (vs 11.4% of VIX). It seems that, when EPU is ordered first, VIX still accounts for all the variability of consumer credit, but it is EPU now to capture a large part of unemployment rate variability and a consistent part of industrial production variability. These results confirm that the relationship between EPU and consumer credit is not as strong as the one with VIX, as already seen in the baseline VARs. Moreover, EPU maintains explanatory power over the variability of industrial production and unemployment rate when VIX is included and ordered second, keeping open the possibility of different explanatory power of these two measures.

3.4 Before and after decoupling of VIX and EPU in 2010

This section analyses the impulse response functions to a shock in both VIX and EPU before and after their decoupling happened in mid-2010, in order to investigate if there is evidence of this decoupling in the effect that these indexes have on the real economy. The sample has been divided into two sub-sets: one runs from January 1990 to June 2010 (before the decoupling) and the other one runs from July 2010 to February 2019 (after the decoupling). The models have been estimated with two lags.

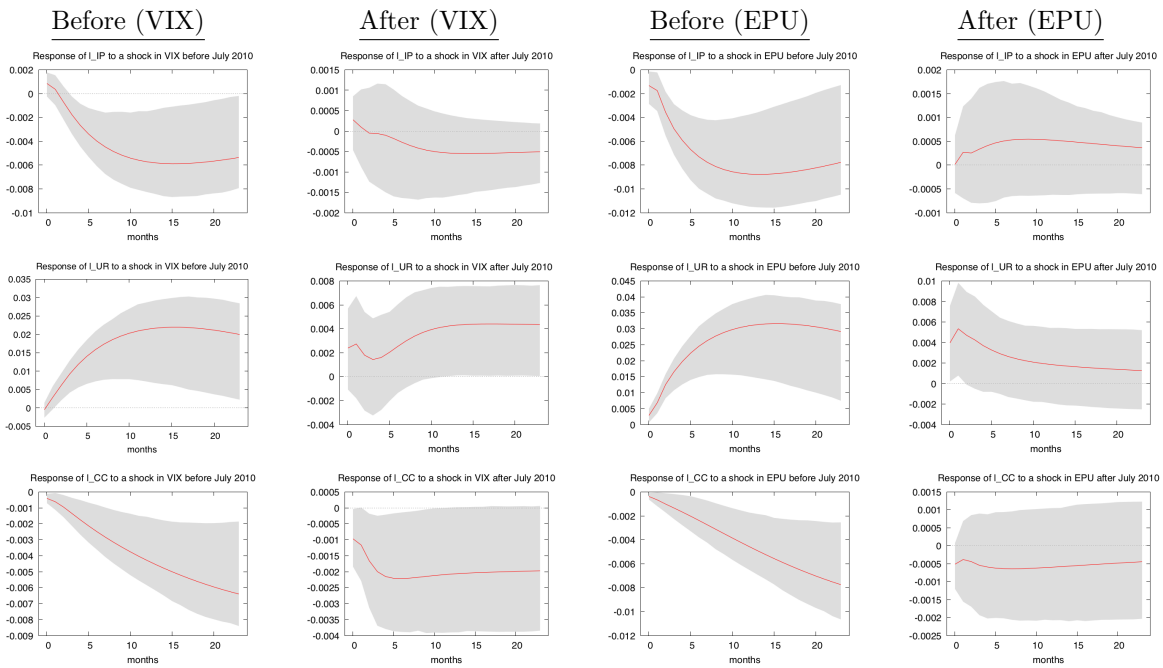

Figure 6: VIX and EPU: Before and after the decoupling. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU and VIX, differentiating between the time period before and after the decoupling started in mid-2010. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: "Before" January 1990 - June 2010 and "After" July 2010 - February 2019

Figure 6 compares the impulse response functions of three macroeconomic variables to a shock in VIX and EPU respectively before and after the decoupling. Before the decoupling, the impulse response functions of the macroeconomic indicators to a shock in VIX or EPU are really similar to the ones observed in the baseline VARs

(see Figure 3 and Figure 4). On the other hand, after the decoupling, the impulse response functions lose almost all the statistical significance. The major difference that is worth pointing out is the behaviour of industrial production. In fact, after the decoupling, the industrial production negatively responds to a shock in VIX, but positively respond to a shock in EPU. This result, although not statistically significant, could represent another sign of the different explanatory ability of VIX and EPU.

Table 4: Forecast Error Variance Decomposition of IP, UR and CC with respect to VIX and EPU before and after decoupling

Before Decoupling						
Horizon (months)	Industrial Production		Unemployment Rate		Consumer Credit	
	VIX	EPU	VIX	EPU	VIX	EPU
1	2	5	0.04	1.6	1.2	1
6	6.4	30.8	14.1	38.3	6.2	5.6
12	16	43.2	25.6	53.9	16.5	16.3
18	19.5	46	28.3	56.9	23.4	26.8
24	20.5	46.1	28.2	56.6	26.7	34
After Decoupling						
Horizon (months)	Industrial Production		Unemployment Rate		Consumer Credit	
	VIX	EPU	VIX	EPU	VIX	EPU
1	0.4	0.001	1.3	3.5	3	0.8
6	0.1	0.6	2.4	9.6	11.7	1.1
12	0.7	1.3	5.8	8.2	15	1.4
18	1.3	1.5	9	6.7	15.7	1.4
24	1.7	1.6	10.8	5.7	15.9	1.3

Note: Table shows the proportion (percentage) of forecast error variance of Industrial Production, Unemployment Rate and Consumer Credit that can be explained by a standard deviation shock in VIX or EPU after 1, 6, 12, 18 and 24 months, differentiating between the time period before and after the decoupling happened in 2010. The model has been estimated with 2 lags.

Table 4 shows the forecast error variance decomposition before and after the decoupling. Before the decoupling, a shock in EPU explains much more variability of the macroeconomic indicators compared to the VIX. After the decoupling, the explanatory power of both indexes is extremely lowered, especially for the EPU.

3.5 Robustness Checks

In this section, several robustness checks are run in order to test the results. The models have been estimated with two lags.

Baseline VAR with trend. Since the results are obtained by inputting the log of the variables into the model, a robustness check is done by estimating the same baseline VARs, but with a trend. Figure 7 displays the impulse response functions of the macroeconomic variables to a shock in VIX and EPU including a trend in the model estimation. As can be clearly seen, the behaviour of the variables is very similar to the one in the baseline analysis, therefore the results are robust.

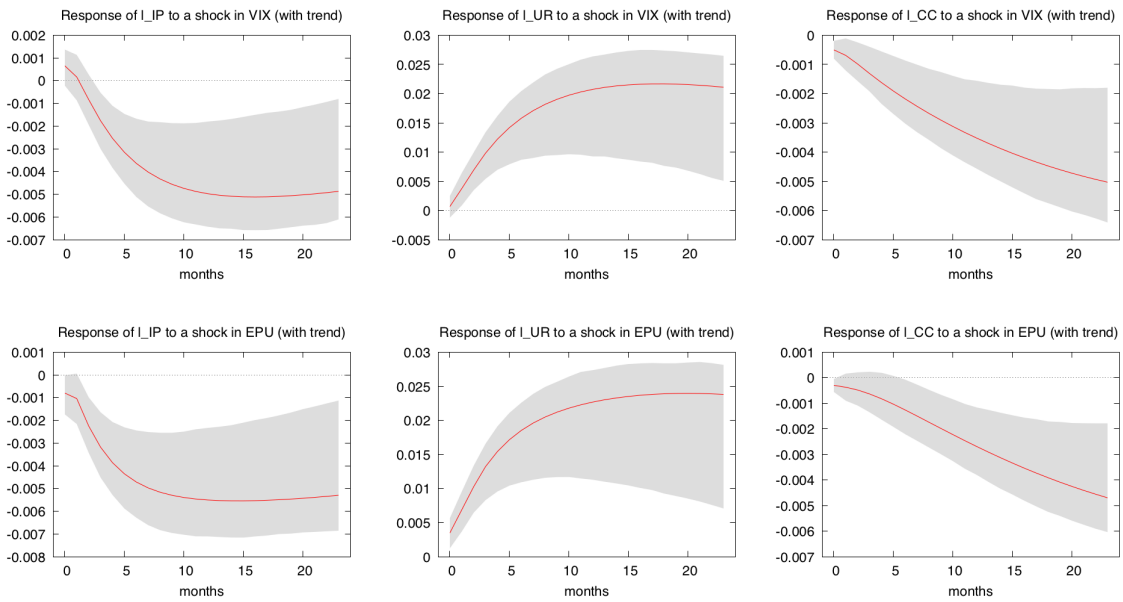

Figure 7: Baseline IRFs with a trend. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU and VIX, including a trend in the model estimation. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

Before and after the financial crisis of 2007. This section analyses the impulse response functions to a shock in both VIX and EPU before and after the financial crisis happened in 2007. The sample has been divided into two sub-sets: one run

from January 1990 to June 2007 (before the financial crisis) and the other one runs from July 2007 to February 2019 (after the financial crisis). The models have been estimated with two lags.

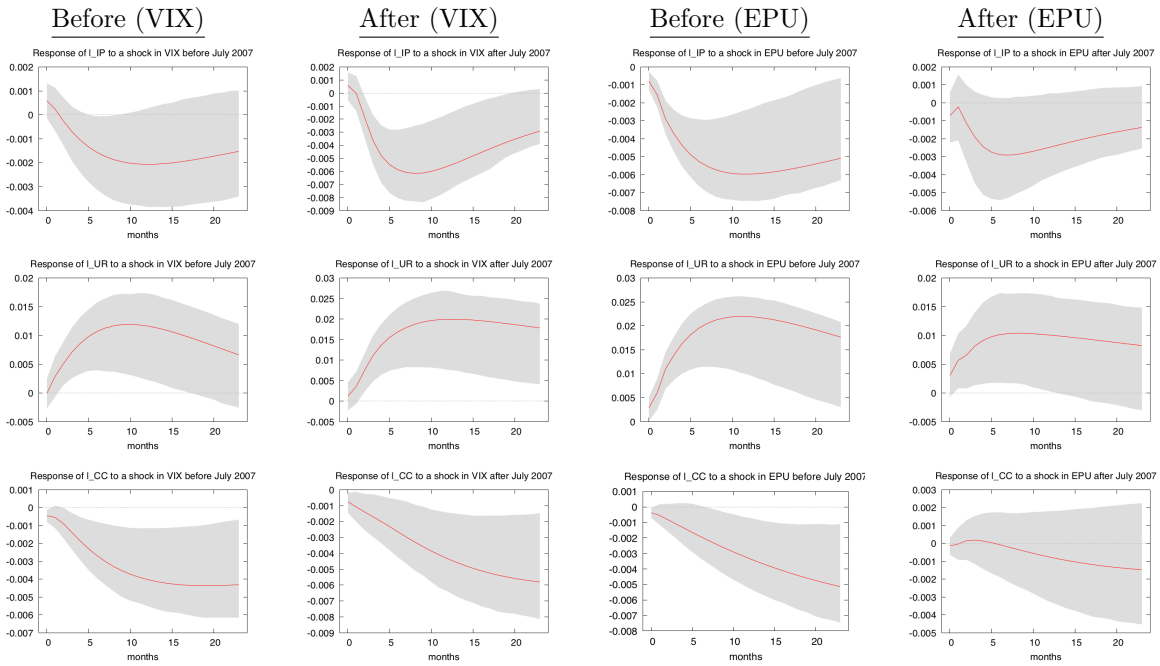

Figure 8: VIX and EPU: Before and after the financial crisis. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU and VIX, differentiating between the time period before and after the financial crisis started in mid-2007. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: "Before" January 1990 - June 2007 and "After" July 2007 - February 2019

Figure 8 compares the impulse response functions of three macroeconomic variables to a shock in VIX and EPU respectively before and after the financial crisis. The responses to a shock in VIX are more pronounced after the financial crisis, whereas the responses to a shock in EPU are less pronounced after the financial crisis. Apart from this, the impulse response functions seem to follow the same behaviour of the baseline VAR both before and after the financial crisis.

Sensitivity to ordering. As explained in Section 2.3, the ordering of the variables matters in a VAR model. For this reason, the robustness of results is checked by

ordering the VIX and EPU indexes last in their respective VARs. The results are shown in Figure 9 and 10 for VIX and EPU respectively. In both cases, the impulse response functions seem to be in line with the one estimated in the baseline VARs (see Figures 3 and 4).

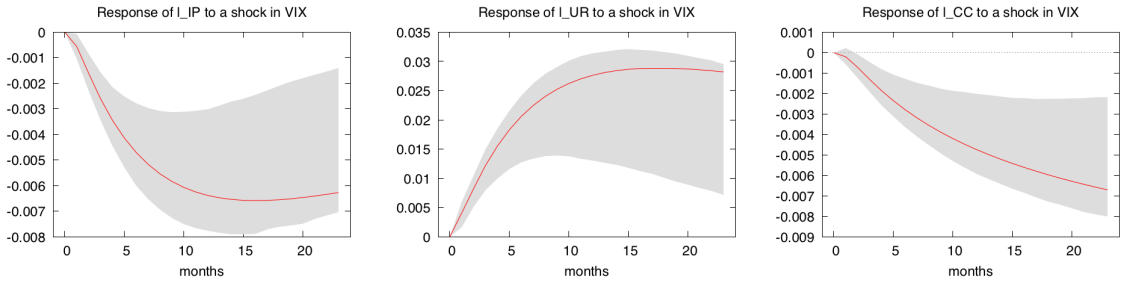

Figure 9: Impulse responses to a shock in VIX (ordered last). Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in VIX, ordering it last. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

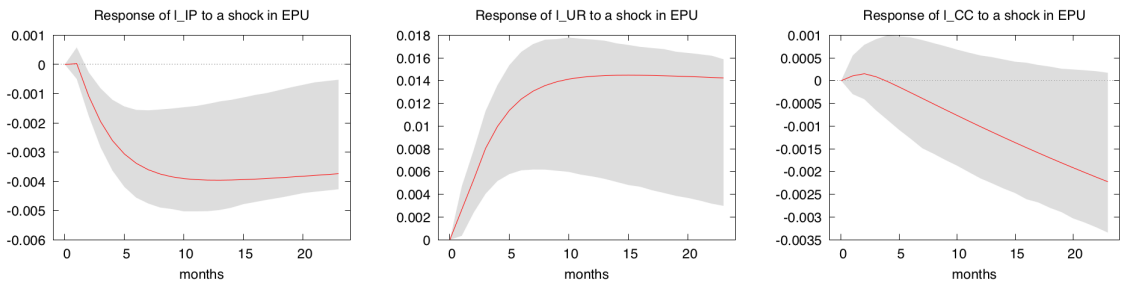

Figure 10: Impulse responses to a shock in EPU (ordered last). Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU, ordering it last. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

First difference responses. In the baseline analysis of the VARs, the macroeconomic variables are entered into the model as their log, meaning that the stationary condition is not respected. In this section the results are checked by inputting in the model the first difference of these variables, thus respecting stationarity. Figures 11 and 12 show that a standard deviation shock in VIX and EPU leads to a drop in

industrial production and consumer credit and an increase in unemployment rate, confirming the robustness of the baseline results.

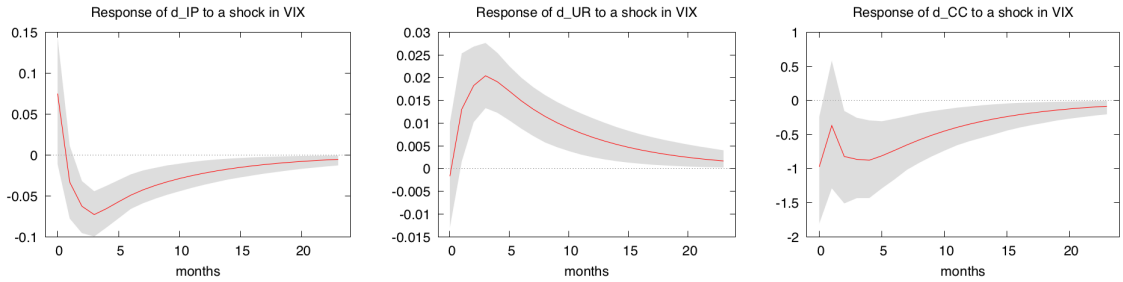

Figure 11: First difference impulse responses to a shock in VIX. Note: impulse responses of the first difference of Industrial Production (d_IP), Unemployment Rate (d_UR) and Consumer Credit (d_CC) to a standard deviation shock in VIX. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

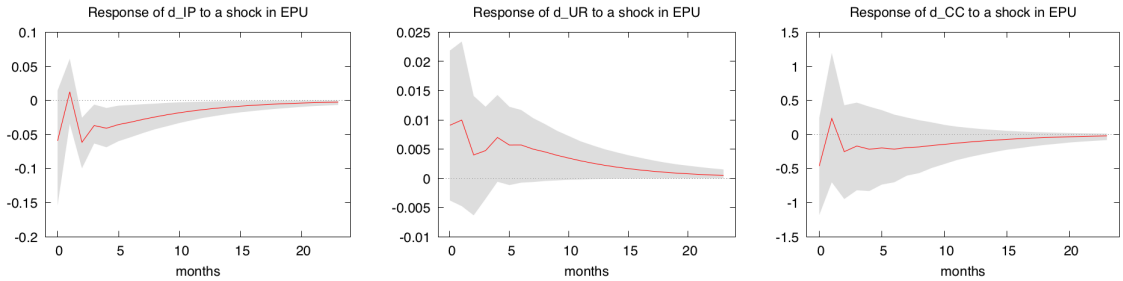

Figure 12: First difference impulse responses to a shock in EPU. Note: impulse responses of the first difference of Industrial Production (d_IP), Unemployment Rate (d_UR) and Consumer Credit (d_CC) to a standard deviation shock in EPU. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: January 1990 - February 2019

Different country: results from the UK. In this section results from a similar analysis in another country are presented to confirm the robustness of the baseline results. The analysis has been conducted on the United Kingdom. As a substitute for the VIX, the implied volatility of the FTSE100 index has been chosen and retrieved from `https://www.investing.com`. The EPU index related to the UK has been retrieved from `https://www.policyuncertainty.com`. The industrial production index has been retrieved from the Organisation for Economic Co-operation and Development (OECD) Database (`https://www.oecd.org`), the unemployment rate

from the Office for National Statistics (https://www.ons.gov.uk) and consumer credit data from the Bank of England database (https://www.bankofengland.co.uk/statistics). The sample period ranges from August 2004 to February 2019, due to the missing data of the implied volatility index prior to this range. The impulse response functions in Figure 13 show similar responses of the macroeconomic variables to shock in VIX and EPU in the UK. However, the results for the impulse response functions to a shock in EPU are not statistically significant.

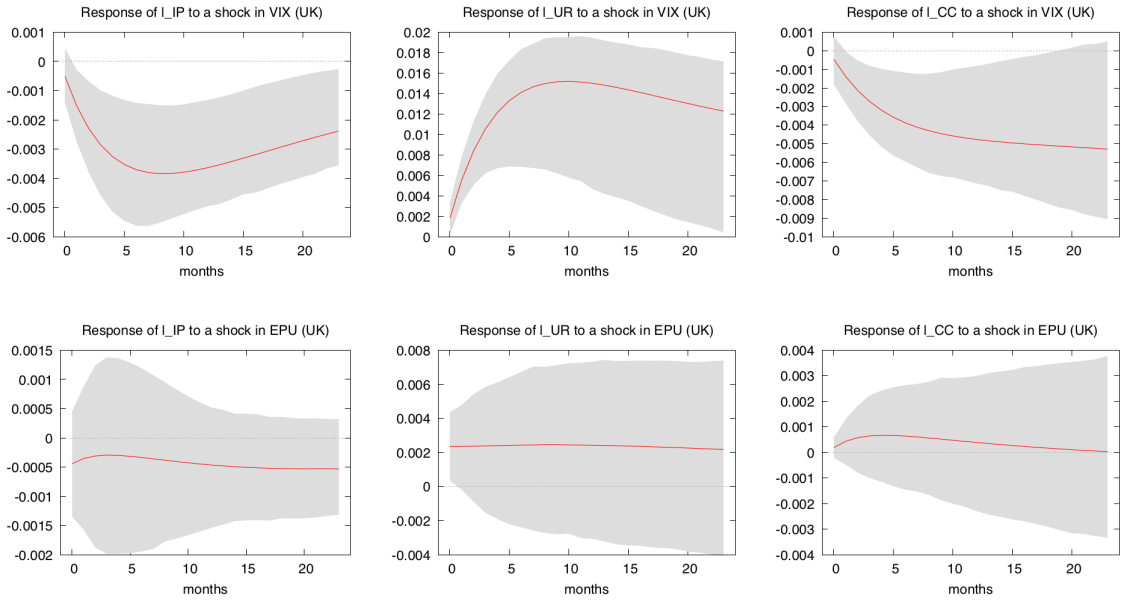

Figure 13: Results from the UK. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in VIX and EPU for the UK. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: August 2004 - February 2019

4 Results and Concluding remarks

This work focuses on the effect of VIX and EPU on the real economy, investigating the differences between these two measures and whether these might be related to the distinction between risk aversion and ambiguity aversion. The empirical results of this work show that both the VIX index and EPU index are countercyclical and can induce recessions: a shock in these measures is associated with a drop in industrial production and consumer credit, and a rise in unemployment rate. So, there is evidence that both measures affect the US business cycle.

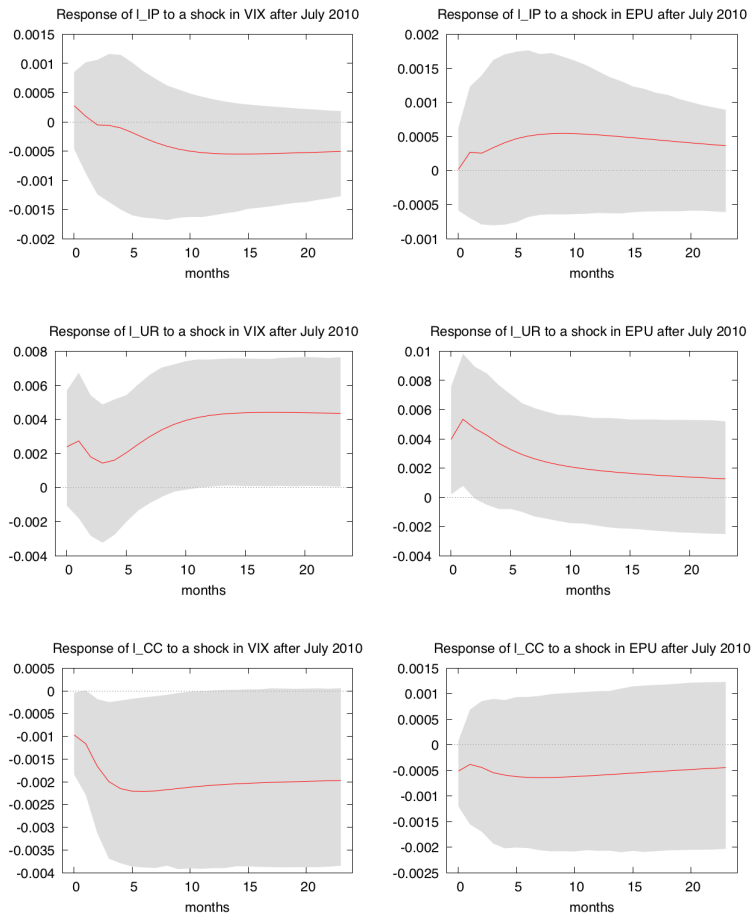

Figure 14: Comparison between impulse response functions to a shock in VIX or EPU after decoupling. Note: impulse responses of the log of Industrial Production (l_IP), Unemployment Rate (l_UR) and Consumer Credit (l_CC) to a standard deviation shock in EPU and VIX after the decoupling started in mid-2010. Red lines indicate the point estimates and grey shaded areas represent the 90 percent confidence interval. The y-axis express percentage points and the x-axis shows the months after the shock. Sample: July 2010 - February 2019

Figure 14 compares the effect on industrial production, unemployment rate and consumer credit of a shock in VIX (left column) and EPU (right column) after the decoupling. The only sign of the presumably different explanatory ability of VIX and EPU is the impulse response function of the industrial production, that negatively responds to a shock in VIX, but positively respond to a shock in EPU. This, together with the low proportion of consumer credit variability explained by the EPU with respect to VIX and the different response of consumer credit to a shock in EPU when controlling for the VIX index (see Section 3.2 and 3.3), represents an evidence of the fact that the EPU index does not capture exactly what the VIX index captures. However, the divergences found in this work are difficult to relate to the difference between risk aversion and ambiguity aversion.

Even if there is some weak evidence that VIX and EPU are capturing different dimensions of uncertainty, there is not enough empirical evidence to officially state that VIX is a measure of risk aversion and EPU is a measure of ambiguity aversion. However, it is worth recalling the fundamental differences between these two measures (and all the other uncertainty proxies) and invite to always check the robustness of results by using different uncertainty proxies.

This work contributed to highlighting the use that has been done of uncertainty proxies in the past literature in structural models and it empirically investigated the differences in the explanatory ability of the two indexes. More broadly, this work empirically showed that the EPU index captures a slightly different dimension of uncertainty than just "risk", and this result could be extended to all news-based measure. Furthermore, it is intuitive that, among news-based measures, the google-search measures are the ones that capture the broadest dimension of uncertainty since they focus on the individual feelings of the general public.

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