THE IMPACT OF ECONOMIC UNCERTAINTY ON HOUSEHOLD CONSUMPTION CHOICES. EVIDENCE FROM EUROPE

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ABSTRACT

This paper is evaluating the impact of uncertainty shocks that are affecting the household behavior in the European Union countries by employing a quantitative approach. By employing a Bayesian VAR model, this paper provides an answer on the importance of the uncertainty shocks on the household consumption choices by using impulse response functions and variance decompositions statistics. The relevance of the study is a major one as it quantifies the impact of the uncertainty pressure on choices consumers make during uncertain times such as the great recession or covid-19 health crisis. Given the current increased focus of the literature on behavioral economics and consumer welfare this paper will provide an answer on consumption by sector increase and decrease as a result of uncertainty shocks.

KEYWORDS: *consumers behavior, consumption, uncertainty, volatility.*

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1. INTRODUCTION

The COVID-19 pandemic has caused huge damages on economies and implicitly on consumer behavior and welfare. This paper is providing fresh and novel evidence of the choice's consumers make during uncertain economic periods. Be it the financial crisis, sovereign debt crisis or covid-19 health crisis, the choices consumers make vary from one sector to another. For example, we can see that there are industries such as Health Care or Alcohol & Tobacco that have a short-term benefit as a result of the uncertainty shock. Most affected industries during uncertain periods are Hotels & Restaurants or Transportation industry. This is confirming that consumers limit their leisure expenses in uncertain periods, what is particularly interesting to point out in these cases is that this happens not as a result of a health crisis, but a broad uncertainty sentiment always has this kind impact on the behavior of consumers.

Up until now, the literature aiming to measure uncertainty has been focused on 2 pillars, one via developing indices of macroeconomic uncertainty (Jurado et al., 2015; Baker et al., 2016; Bekaert et al., 2020) or by choosing proxies that include full market information on economic or financial sentiment in real time (Bonciani & Van Roye, 2016; Horvath & Zhong, 2019) by using proxies like the VIX index or VSTOXX index that are showcasing the stock market expectations in terms of volatility for the United States & the Euro Area. Bloom (2009) is presenting stock market volatility as a very widely use proxy (Leahy et al.,1996; Bond & Van Reenen, 2007) for measuring uncertainty. Baker et al. (2020) are identifying three indicators: stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty in business expectations surveys, which they classify as containing real-time forward-looking uncertainty measures. For the current paper, the proxy for uncertainty will be represented by the VSTOXX index (the implied volatility of the Euro Area stock market) indicator which is expressing the future expectations for stock market

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volatility in the Euro Area. The chosen proxy for uncertainty in this paper is bringing it's own big advantage of having full market & economics information included in real time. This is at the same time a parsimonious approach that is making the measurement of the core indicator of the study possible, and it is avoiding spurious results as a consequence of indices estimation. This paper is employing a Bayesian VAR model with a normal-diffuse prior that will be capable to measure the shocks on each household consumption segment via variance decomposition and impulse response functions statistics. The models employed in this paper are constructed by closely following the computational approach from Dieppe et al. (2018) to simulate all the 9 VAR models presented in this paper. While all the estimated VAR models are stable with no roots outside the unit circle, the other reason for using a normal-diffuse prior is still to have a parsimonious approach across the board which is assuming that the variables in the model follow an unobservable trend and they cannot be predicted. According to Nam et al. (2021) "S&P 500 implied volatility (VIX) significantly depress U.S. households' consumption" which confirms the valuable information the VSTOXX index is bringing to the current study.

While there are numerous papers studying the impact of uncertainty on household consumption, there is of course the other side of the story as well where the consumers decrease their consumption not necessarily because their income is decreasing, but when they increase their own need for savings, Aaberge et al. (2017) presents evidence that "*a surge in political uncertainty resulted in significant temporary increases in savings among urban households in China*", with this in mind the current paper supports that a broad sentiment of uncertainty does not necessarily lead to economic and financial crisis.

The reminder of the paper is organized as follows: Section 2 presents Bayesian VAR model used in the estimations; Section 3 discusses the data and the results while Section 4 concludes the paper.

2. MODEL SPECIFICATION

This section is summarizing the form of the general VAR model for the particular case of this paper and the form of the Bayesian VAR with the normal-diffuse prior.

2.1 Formulation of the general VAR model

There are 9 VAR models estimated in this paper contain 2 endogenous variables, 1 lag, and one vector of exogenous regressors. In a compact form the general model can be summarized in the following equation:

$$Y_t = \mathrm{A}Y_{t-1} + CX_t + \varepsilon_t (1)$$

Where:

Y is a matrix of dimension $n \times 1$ (2×1 in this particular case) and it represents the vector of endogenous variables

A is a matrix of parameters with dimensions $n \times n$ (2×2 in this particular case)

C is a matrix of dimension $n \times m$ (2×2 in this particular case) and X_t is a vector of constant exogenous regressors (constant terms)

ε_t is the vector of residuals, where: $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{n,t})$ with $\varepsilon \sim N(0, \Sigma)$

2.2 The Bayesian VAR Model with normal-diffuse prior

In order to compute the shape of the posterior distribution this paper is closely following the computational steps developed in Dieppe, et al. (2018). To obtain the posterior distribution for β two elements will be necessary: the likelihood function $f(Y \mid \beta)$ for the data and the prior distribution for β : $\pi(\beta)$. By closely following the computational steps developed in Dieppe, et al. (2018), one should start from the likelihood function, this formulation implies that the residuals follow a normal multivariate distribution of mean equal to 0 and a variance-covariance matrix $\overline{\sum}$. In this case the data would follow a normal multivariate distribution as well of mean $\overline{X}\beta$ and a variance-covariance matrix $\overline{\sum}$. Therefore, the likelihood function for Y will have the following form:

$$f(Y|\beta,\bar{\Sigma}) = (2\pi)^{-nT/2}|\bar{\Sigma}|^{-1/2}\exp\left[-\frac{1}{2}(Y-\bar{X}\beta)'\bar{\Sigma}^{-1}(Y-\bar{X}\beta)\right](2)$$

Ignoring the constant terms, equation (3) will be simplified and will take the following form:

$$f(Y|\beta,\bar{\Sigma}) \propto \exp\left[-\frac{1}{2}(Y-\bar{X}\beta)'\bar{\Sigma}^{-1}(Y-\bar{X}\beta)\right](3)$$

The prior β will follow a normal multivariate distribution as well of mean β_0 and variance covariance matrix Ω_0:

$$\pi(\beta) \sim N(\beta_0,\Omega_0)(4)$$

Similar to the previous approach the constant terms will be excluded and the simplified equation will take the following form:

$$\pi(\beta) \propto \exp\left[-\frac{1}{2}(\beta-\beta_0)'{\Omega_0}^{-1}(\beta-\beta_0)\right](5)$$

By combining the likelihood with the prior, the posterior distribution will take the form of a multivariate normal distribution:

$$\pi(\beta|Y) \propto \exp\left[-\frac{1}{2}\left(\beta-\bar{\beta}\right)'\bar{\Omega}^{-1}\left(\beta-\bar{\beta}\right)\right](6)$$

$$\pi(\beta|Y) \sim N\left(\bar{\beta},\bar{\Omega}\right)(7)$$

One wants to remain agnostic about the value of $\sum$. Thus, the main change will be the distribution for $\sum$ which will be now defined by the *"Jeffrey's"* distribution or diffuse prior:

$$\pi(\Sigma) \propto |\Sigma|^{-(n+1)/2}(8)$$

The peculiarity related to this prior distribution would be that it is a non-informative distribution, which means that the data will bring the biggest contribution when it comes to the estimated results.

By following the above steps as exposed in the previous section and by starting from the likelihood function and the prior distribution this will lead again the posterior to take the form of a normal multivariate distribution:

$$\pi(\beta|Y) \propto \exp\left[-\frac{1}{2}\left(\beta-\bar{\beta}\right)'\bar{\Omega}^{-1}\left(\beta-\bar{\beta}\right)\right](9)$$

$$\pi(\beta|Y) \sim N\left(\bar{\beta},\bar{\Omega}\right)(10)$$

3. DATA AND RESULTS

The data used is represented by annual consumption data from Eurostat for Total Household consumption in from the European Union and the following consumption segments: Food, Hotels & Restaurants, Personal Care, Clothing & Footwear, Health Care, Transportation, Communication and Alcohol & Tobacco. For Uncertainty as pointed in the introduction the VSTOXX50 implied volatility index is used. The final input data from the model is represented by the percentage change of each variable from T0 to T1. The daily series of the VSTOXX50 volatility index is aggregated to the annual level in order to be make possible the simulation along with annual consumption data for the EU countries Eurostat. The VSTOXX50 index is sourced from the Refinitiv database.

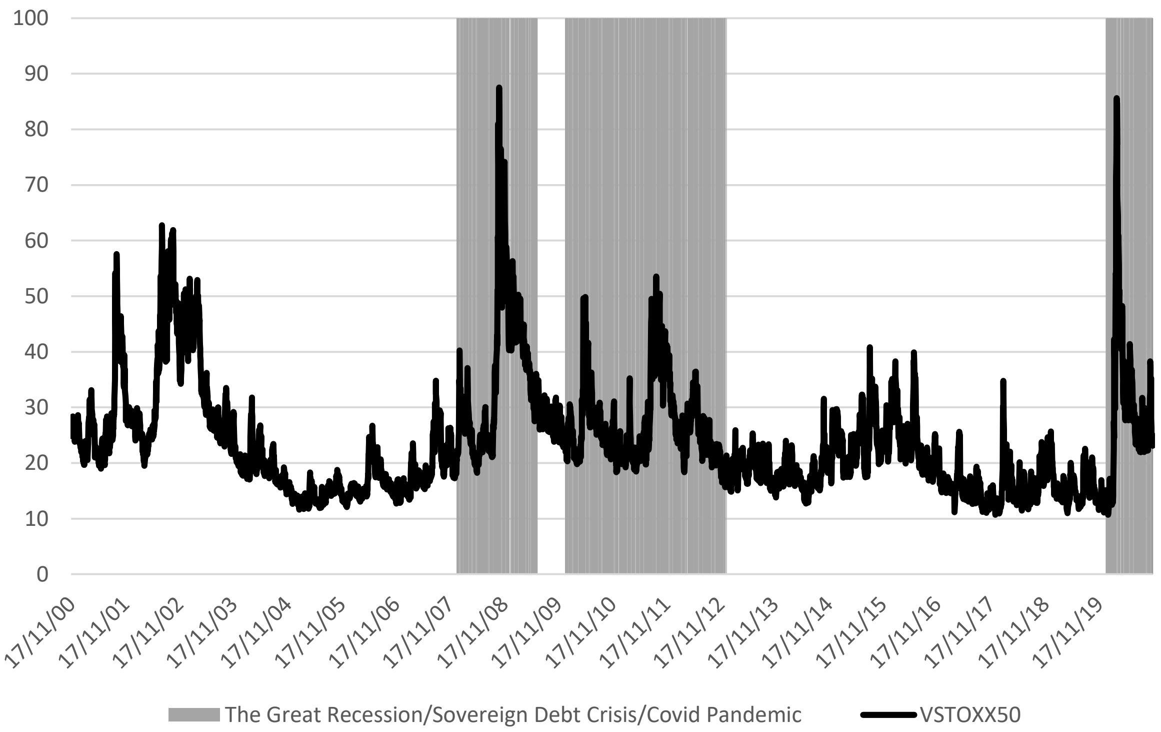

Figure 1. VSTOXX50 index
Source: Refinitiv Database

A very important correlation can become visible from Fig.1 which is exposing the 20 year data for the VSTOXX50 index, here the stock market implied volatility picks up when uncertainty is high, but not mandatory in a financial crisis. This happened both in The Great Recession, the Sovereign Debt Crisis and the current Covid-19 pandemic and it is a confirmation that the implied volatility index does not necessarily represent a financial crisis meter, as this was not the case in the Covid-19 pandemic, but it confirms one more time that it serves as a very valuable measurement for overall uncertainty sentiment in real time.
The total household consumption in the European Union (28 countries group) is exposed in Fig 2. and measured in billion of euros. This of course is converted to year over year percentage change in order to simulate the Bayesian VAR models.

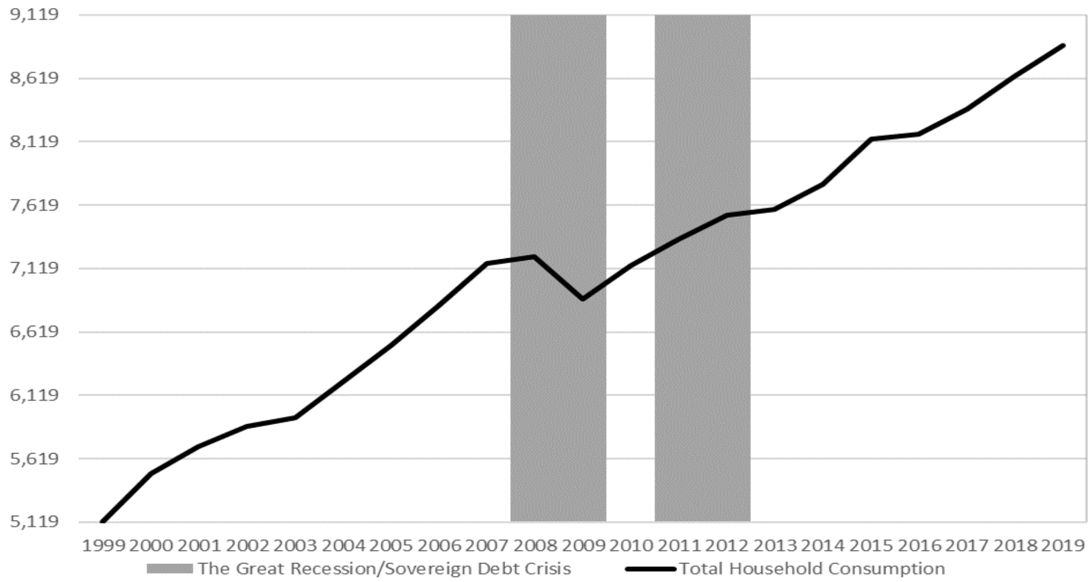

Figure 2. Total household consumption in the European Union
Source: Refinitiv Database

According to the estimated results, several findings come to light. First, In Fig 3. there is the sequence of importance for the impact of uncertainty on each consumption aggregate, which should be read as the uncertainty impact on each item while the rest is assumed to be constant. The above pie chart is exposing what expectations should companies from each industry should have in the event of an uncertainty shock and prepare in relation with that.
As we can see the most affected segment are the Hotels & Restaurants. This means that in uncertain periods of time, consumers have become very reluctant to spend money on leisure expenses, they focus more on the necessary rather than on the wellbeing, the same goes for travelling as transportation is of course the second block that is dropping in this scenario.
But not all uncertainty shocks are meant to have negative impact on consumption. Anticyclical industries such as Health Care or Alochol & Tobacco are taking benefit from the disorder. This can become visible in Fig 4. which is relevant to understand that uncertainty is impacting in a negative manner the consumption of: Food, Hotels & Restaurants, Personal Care, Clothing & Footwear, Communications and Transportation. And in a positive manner most significantly the Health Care with positive pickups in consumption of almost 20% in the first year.

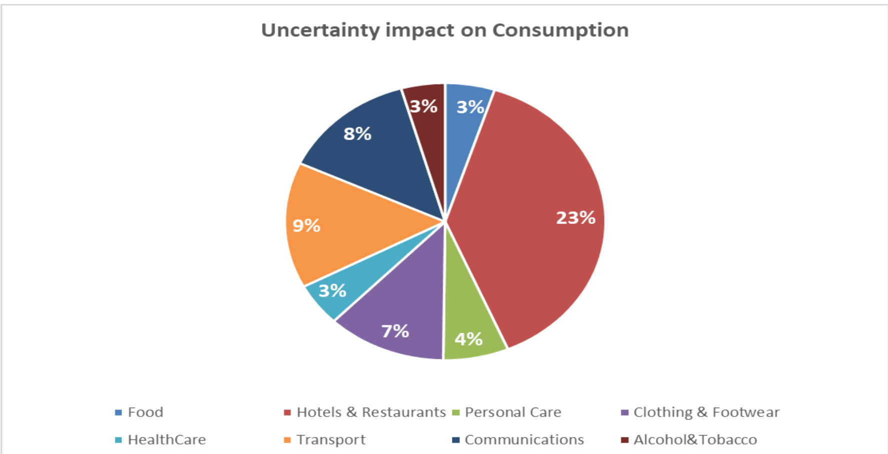

Figure 3. Forecast variance decomposition - Uncertainty impact on consumption by segment
Source: Estimated results of the author

Table 1. Consumption by sector (billions of euro)

Year	Food	Horeca	Personal Care	Clothing & Footwear	HealthCare	Transport	Communications	Alcohol& Tobacco	Total Household Consumption
1999	583	416	113	300	160	703	125	227	5119
2000	614	456	121	316	170	752	141	239	5504
2001	647	477	126	324	181	768	155	247	5715
2002	665	493	132	333	192	784	165	254	5873
2003	672	497	136	330	199	786	169	253	5945
2004	698	521	143	338	214	831	179	255	6227
2005	719	543	145	347	222	879	186	264	6510
2006	742	570	154	361	225	922	191	271	6826
2007	778	597	163	376	241	959	197	281	7157
2008	805	588	162	369	252	960	198	283	7216
2009	777	555	157	348	252	884	193	281	6881
2010	795	573	169	360	264	913	198	292	7147
2011	815	589	173	366	276	964	198	302	7352
2012	839	607	177	369	284	979	198	310	7543
2013	852	612	177	371	291	970	192	310	7585
2014	865	641	184	384	300	1002	189	311	7786
2015	890	683	191	400	312	1032	194	322	8137
2016	899	695	196	399	317	1039	195	322	8178
2017	921	731	200	406	327	1083	198	326	8375
2018	950	759	205	410	337	1144	199	335	8638
2019	977	792	212	421	349	1177	200	343	8878

Source: Eurostat Database

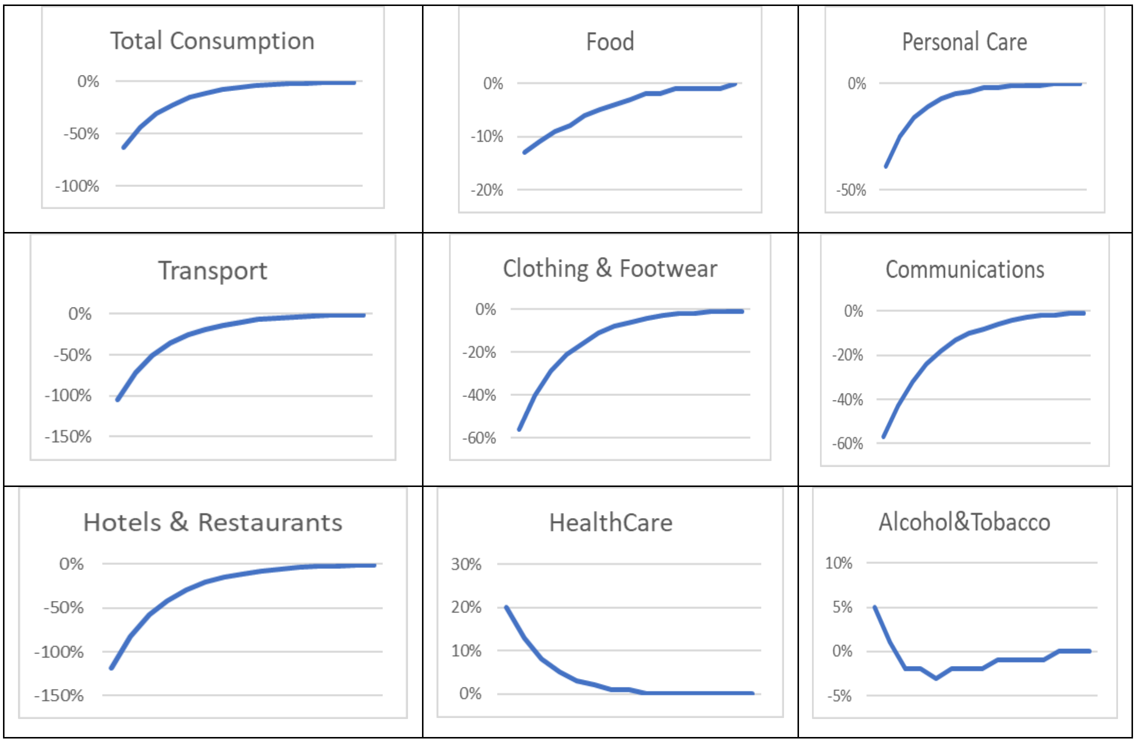

Figure 4. Impulse response functions of uncertainty shocks on each consumption aggregate
Source: Estimated results of the author

4. CONCLUSIONS

This study offers empirical evidence on the impact of the uncertainty shocks on consumption segments in the European Union. By employing a Bayesian VAR model, the study is providing evidence that most impacted consumption segments by uncertainty shocks are the ones connected to leisure and wellbeing of consumers. This means that as uncertainty get's more intense in the society, consumers activate a rationale pattern for their consumption behavior, where they are more likely to give up rather on leisure than on food, and start taking care more of themselves in the healthcare side, an effect which can be interpreted also as health risk for the population in case of high uncertainty periods. Even though the results are indicating the chances are low, there are increases in alcohol & tobacco consumption, which suggests that there is a small degree of welfare drop that needs to be supplemented by psychoactive substances in uncertain periods.

Therefore, the current study presents relevance both for the behavioral economic research field and for the private companies involved in the studied industries. Overall, it can be seen that uncertainty is impacting consumption in a negative manner, and it's important to mention that periods with high uncertainty can be correlated with periods of economic and financial crisis, but this is not a requirement, in this periods there is just a broad opinion than there might be the case of a crisis.

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