Iranian Journal of Economic Studies, 11(2) 2022, 323-350

Shiraz University

Iranian Journal of Economic Studies

Journal homepage: ijes.shirazu.ac.ir

Measuring Economic Uncertainty in Iran: Integrating Economic and Institutional Factors

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Article History

Received date: 18 December 2023
Revised date: 29 April 2024
Accepted date: 13 May 2024
Available online: 2 June 2024

JEL Classification

D81
C53
C32
E02
C87

Keyword

Economic uncertainty
Stochastic processes
Dynamic factor models
Institutional factors

Abstract

Uncertainty is a controversial issue in the philosophy and methodology of economics. Since economic uncertainty is not directly observable, quantifying it is confronted with significant complexities. A common method in this context involves computing the proxy of uncertainty using time series models. Within this framework, the conditional volatility of the unpredictable components of time series is considered as an uncertainty measure. In this regard, the basic forecasting model should be specified in a way that its forecast errors lack any predictable content. In previous studies, the focus has solely been on economic and financial variables in computing the uncertainty measure, while the role of institutional factors has been neglected in the forecasting model. Meanwhile, based on economic literature, institutions play an important role in controlling and reducing uncertainty. Therefore, in the present study, the economic uncertainty measure is extracted based on a Large-dimensional dynamic factor model, employing a set of 72 macroeconomic and institutional time series for the Iranian economy. The data are quarterly and span the period 1991:Q2-2022:Q1. The results indicate that overlooking institutional factors in the forecasting model can lead to an overestimation of uncertainty. Our perspective enhances the accuracy of uncertainty measurement and provides a more comprehensive understanding of the determinant factors of uncertainty.

Highlights

- The FAVAR model is advantageous for measuring economic uncertainty due to its ability to extract latent common factors from data sets, allowing for a more accurate distinction between predictable and unpredictable components of time series.
- This study shows that overlooking institutional factors in uncertainty measurement models leads to overestimation of uncertainty. Incorporating institutional variables along with economic and financial variables improves forecast accuracy.

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DOI: 10.22099/ijes.2024.49143.1946

1. Introduction

Uncertainty has been a controversial issue in the philosophy and methodology of economics. However, there is no consensus among economists about the meaning of uncertainty and its relevance to the advancement of economic theory (Lawson, 1988). Uncertainty in economics has different facets. When it comes to uncertainty, the economic discipline falls apart and discussions become highly emotional (Rosenberg, 2013). The concept of uncertainty has been of particular importance in economic literature, and some researchers interpret uncertainty as a nail in the coffin of neoclassical deterministic economics (Dow, 2008). Therefore, it is no surprise that most economists' view of uncertainty is political and dogmatic. On the one hand, some seek to save the neoclassical uncertainty paradigm; and on the other hand, there are those who intend another uncertainty paradigm to replace mainstream economics—thus, there is no consensus in this regard (Hodgson, 2009). The disagreements surrounding this issue have been a challenging debate since the 1930s and continue to exist. From that time onward, the concept of uncertainty has been extensively discussed in philosophy and economic methodology. After that, it has been paid less attention in some periods, and with the arrival of third millennium, this discussion has been marginalized and neglected (Hodgson, 2011).

The financial crisis of 2007-2008 again attracted the attention of researchers to this challenging debate in the Philosophy of economics, during this period, increasing uncertainty was recognized as one of the main reasons for this crisis. This crisis can be considered as a milestone in the studies of uncertainty because during this period academic research on uncertainty increased noticeably. Some scholars provide evidence to support the idea that the relatively high level of uncertainty has been a reason for the slow growth of the world economy during this period (Bloom, 2009; Cover, 2011). But how does the level of uncertainty that macroeconomics confronts affect its behavior? The early literature emphasizes the real options channel (uncertainty in investment decisions) (Bernanke, 1983; Dixit, 1989; Pindyck, 1991). Recently, various studies have also confirmed such findings, demonstrating that with increased uncertainty, firms tend to be more cautious in investment and hiring (Bloom et al, 2018). In addition, consumers, with increasing uncertainty, decrease their consumption expenditure and simultaneously increase their precautionary savings (precautionary savings channel). Considering these effects, some researchers interpret uncertainty shocks as aggregate demand shocks (Challe et al., 2017; Leduk & Liu, 2016). Such interpretations can lead to the emergence of extensive discussions regarding the process of uncertainty and its impacts. However, the explanation of the role of uncertainty in the creation of crises and its application in economic theory has been largely left unanswered (Kohn, 2017). The occurrence of this crisis has motivated researchers to measure the uncertainty. Recently, there has been a burgeoning number of studies conducted to introduce a proxy for uncertainty, which also brought illuminating results. The emphasis of this research is on the use of appropriate proxies in modeling. In fact, the uncertainty proxy should be set in a way that is both computable and economically interpretable. In addition, uncertainty measurement modeling should be done in a way that be congruent with its nature and theoretical concept.

Generally speaking, theoretical models related to uncertainty measurement are based on two classical and Keynesian approaches. Despite the difference in concept, there is a relative correlation between the output measures of these two approaches. In the recent decade, efforts have been made to highlight the empirical distinctions between these two concepts of uncertainty (Bekaert et al., 2013; Jurado et al., 2015; Rossi et al., 2018; Bekaert et al., 2022; Boeck et al., 2023). The evidence shows that the empirical results are significantly different with each of these criteria, and this issue shows that the appropriate measure of uncertainty can play a significant role in the results of empirical studies. The importance of time-varying economic uncertainty and its role in macroeconomic fluctuations have been among the most discussed issues in the last decade. In the new literature, uncertainty is defined as the conditional volatility of a disturbance that is unpredictable from the perspective of economic agents (Jurado et al., 2015). Economic uncertainty can be evaluated in different fields, including general and macroeconomic uncertainty, macroeconomic variables uncertainty, and economic policy uncertainty. Accordingly, uncertainty is examined as a fundamental factor in the formation of the behavior of economic agents.

In general, an uncertainty measure should include three features that can be considered an appropriate proxy of uncertainty. First, it does not include forecastable variations[1]. Second, it should be related to the future, and third, it should be time-varying (Jurado et al., 2015). Therefore, in measuring uncertainty, the above features must be observed in the modeling to avoid potential bias in the results. Among the different models, dynamic factor models play an important role in monitoring real-time macroeconomic events and forecasting these events in the future. The advantage of these models, compared to standard forecasting models, is that by extracting common hidden factors from the data set, it is possible to forecast macroeconomic time series more accurately and reduce the bias caused by the omitted information (Stock & Watson, 2016). Based on this, some researchers have introduced proxies to measure uncertainty by using these models (Jurado et al., 2015; Carriero et al., 2018; Ludvigson et al., 2021). In these studies, a modest number of factors estimated from an extensive collection of economic time series, and the uncertainty measure has been computed by designing a forecasting model. Despite several advantages, one of the issues that has been overlooked in these studies is the emphasis on macroeconomic and financial variables, and ignoring institutional variables in the computation of the uncertainty criterion. Meanwhile, in economic literature, institutions play a significant role in controlling and decreasing uncertainty. Institutions encompass formal rules like laws imposed by governments, as well as informal rules like

[1] Based on the definition, the uncertainty process is unpredictable from the perspective of economic agents, therefore, the uncertainty proxy should not include forecastable variations.

culture and values that arise from social structures (North, 1991). According to institutional theory, agents have a limited capacity for evaluating situations that could impact the decision-making process, and to reduce uncertainties, they depend on institutions to legitimize their actions (Moura et al., 2009). Therefore, to incorporate the role of formal rules and informal rules in shaping uncertainty, it is necessary to include institutional variables in uncertainty measurement modeling. In this regard, the present study aims to compute the uncertainty criterion by considering a large number of macroeconomic series and institutional indicators for the economy of Iran. This comprehensive breakdown provides a framework, enabling thoroughly examining economic uncertainty trends and dynamics. For this purpose, the present study attempts to evaluate the role of institutional indicators in measuring this latent stochastic process by using a Factor Augmented Vector Autoregression (FAVAR) Model, while computing the uncertainty criterion. The main contribution of this study lies in evaluating the role of institutional factors in shaping uncertainty. Additionally, the computation of a comprehensive measure of macroeconomic uncertainty for the Iranian economy is another significant aspect of this research. The remainder of this paper is divided into several sections. The second section provides an overview of the theoretical framework and literature review. The third section delves into the econometric methodology. The fourth section presents the empirical research results. Finally, in the fifth section, the results are discussed and the authors' conclusions are provided.

2. Theoretical Framework

When discussing uncertainty and its implications on economic activities, there are two primary distinctions among various economic theories: (1) the analyst's cognitive grasp of the external economic reality where decision-makers operate, and (2) the ability of agents to comprehend that reality (Davidson, 1996). Yet the fundamental question is how is economic reality defined. Is this reality predetermined, immutable, and ergodic (i.e., knowable over time)? Or is it mutable, unknown, and non-ergodic? A review of the literature in this field reveals that economic schools have diverse and controversial viewpoints regarding economic reality and, consequently, the concept of uncertainty.

2.1 Concept of Uncertainty and Economic Schools

Davidson (1998) introduced the first conceptual classification of uncertainty. Although there has previously been research on uncertainty and the interpretation of its concept, in this study, he has highlighted the conceptual differences between the classical concept and the Keynesian concept of uncertainty. According to Davidson's perspective, the ability of economists to elucidate matters such as the significance of money, liquidity, and the persistence of unemployment in the market economy is contingent upon the concept of uncertainty adopted by the analyst.

The classical economists of the 19th century operated under the assumption of a world characterized by perfect certainty. In this framework, all economic agents were presumed to possess complete and accurate knowledge of an externally determined economic reality, which governed all economic outcomes across past, present, and future. This external economic environment was perceived as unchangeable, impervious to alterations resulting from human activity. Similar to the deterministic laws governing celestial mechanics in Newtonian physics, the trajectory of the economy was believed to be determined by immutable and timeless natural laws (Davidson, 1999, p. 3). At the beginning of the 20th century, classical economists tended to substitute the notion of 'certainty equivalent' and 'probabilistic risk premium' for the perfect knowledge of previous classical theory. Today's orthodox economists associate uncertainty in economics with objective probability distributions that govern future events, arguing that these distributions are entirely known to everyone (Lucas & Sargent, 1981; Machina, 1987). In the orthodox economics of the 20th century, economic data are typically viewed as realized parts of time series that are produced by ergodic[1] stochastic processes. In this framework, standard deviation is used as a criterion for measuring uncertainty. This representation of uncertainty enables orthodox economists to maintain much of the analytical methods established under the previous assumption of perfect certainty, despite rejecting the perfect certainty model. Paul Samuelson (1969) also emphasized the acceptance of the ergodic theorem as a vital element of the scientific method in economics. Currently, following Samuelson and Lucas, the majority of mainstream economists—while rejecting the full certainty model— accept the existence of a predetermined reality that can be described through unchangeable conditional probability functions, as a universal truth (ergodic world).

John Maynard Keynes (1936) in this field initiated a revolution in economics by introducing the "general theory" as a substitute for classical theory. He argued that the distinction between probabilistic risk and uncertainty holds profound implications for comprehending: 1) the operations of the market economy, and 2) the government's role in influencing market outcomes through intentional legislative policies. According to Keynes's analysis, uncertainty will prevail whenever the full ramifications of present economic decisions extend into the distant future, and economic behavior cannot be reduced to "the weighted average of quantitative benefits multiplied by quantitative probabilities". In contrast to contemporary orthodox economists, Keynes did not use the idiom of stochastic processes to develop his uncertainty concept (Davidson, 1999, p. 34). Keynes (1937) stated that uncertainty occurs when there is no scientific basis to form any computable probability (non-ergodic world). According to Keynes (1937), there

[1] In essence, a system is ergodic if ergodicity holds within it. Ergodicity means that every measurable and defined subset of the system's state space converges to its average values over time. This concept is characterized by time ergodicity, spatial ergodicity, and mixing ergodicity.

is no scientific basis for forming any computable probabilities about future events—a situation that Keynes described it as: 'We simply do not know'.

From the Post Keynesian perspective, the world is also non-ergodic meaning that each historical event is unique and non-repetitive. Under such conditions, the probability rules cannot be applied. From this perspective, the world contains 'kaleidic' changes and fundamental discontinuities[1]. Post-Keynesians, following Keynes (1933), distinguish between situations involving risk and those involving uncertainty. From their perspective in situations of uncertainty, it is not possible to formulate a meaningful probability distribution. They argue that in the framework of the rational expectations hypothesis, it is assumed that economic agents can formulate probability distributions of the outcomes of various situations, hence this perspective belongs to the world of risk. Accordingly, in the ne w classical models, the problem of fundamental uncertainty is overlooked. According to the Post Keynesian, the real world is characterized by fundamental uncertainty, which means that the conclusions made on the basis of the models using the rational expectations hypothesis are useless. Likewise, the Austrian school of thought also severely criticizes the hypothesis of rational expectations (Snowdon & Vane, 2005, p. 229).

According to the new institutionalists, economic realities are analyzed by considering the role of uncertainty. Institutionalists maintain that uncertainty is an aspect of the nature of societies. In this approach, the fundamental definition of uncertainty depends on the ontological understanding of economic reality. An economic event (future) may not be predictable for economic agents due to structural changes (human creativity, technology, or crises). This means that some information related to an economic event cannot be obtained even at the moment of critical decision-making. Therefore, the ontological aspect of uncertainty is the type of knowledge that economic agents can (or cannot) have in uncertain situations. Within such an environment, the fundamental question is whether uncertainty implies a total absence of knowledge and complete ignorance. In the analytical framework of institutionalists, uncertainty does not mean complete ignorance (about an event in the future) and this problem depends on the performance of related institutions. According to institutionalists, institutions can establish the context for understanding the ontology of economic realities, which in turn leads to a more accurate epistemology of economic realities. Therefore, the concept of fundamental uncertainty is related to institutions (Dequech, 2001). In short, according to institutionalists, including the role of institutions in economic analysis can move the economic agents from a non-ergodic world to an ergodic (understandable) world.

[1] Here the term 'Kaleidic' refers to the ever-changing nature and situation of an economy. George Shackle (1974) held a relatively radical interpretation of Keynesian economics, believing that uncertainty is the cause of 'initial kaleidic'.

2.2 Measuring Economic Uncertainty

There are various methods for measuring uncertainty in the economic literature, each with strengths and weaknesses. Some of these methods are preferred over others depending on their particular application. However, the best options are not always available., In the sense that researchers sometimes have no alternative but to choose the second best. In general, the methods of measuring uncertainty can be categorized as survey-based, model-based, and news-based.

In the survey-based approach, the uncertainty is measured based on the data collected through the survey. The Philadelphia Fed Survey of Professional Forecasters (launched in 1968) and the European Central Bank Survey of Professional Forecasters (launched in 1999) are two reputable probability surveys. Based on survey data, different measures of uncertainty can be computed. Among these criteria, we can mention the standard deviation of point forecasts (which is known for the disagreement of forecasters) and the average of squared individual forecast errors. The initial research in this area goes back to the study of Zarnovitz and Lambros (1987) and Bomberger (1996). In these studies, the criterion of 'disagreement among forecasters' was introduced to measure uncertainty. However, in subsequent studies, this criterion was augmented by Bomberger (1999) and Giordani and Soderlind (2003). Also, Menkio et al, (2003) have suggested the difference between the 25th and 75th percentiles of inflation forecasts as a measure of inflation uncertainty. Rossi and Sekhposyan (2015) — relying on the survey of professional forecasters and distinguishing between expected and unexpected movements of macroeconomic variables— have proposed uncertainty relative to predicted outcomes as a measure of uncertainty. Their measure is based on how the concept of unexpected mistakes in forecasting macroeconomic variables is commensurate with their historical distribution. Altig et al. (2022) have constructed a measure for business uncertainty based on a survey over firm-level. Bachman et al. (2013) have shown that the criterion of 'disagreement among professional forecasters' can be an appropriate proxy for uncertainty. Anzuoni and Rossi (2020) argued that if surveys contain information about the probability distributions of the future evolution of that variable, then surveys can provide the cleanest measure of uncertainty, assuming that forecasters have no incentive to present biased forecasts. However, Rich and Tracy (2010) showed that there is a weaker correlation between this measure and other uncertainty proxies.

Some researchers adopting time series econometric models have introduced the volatility of actual variables as a measure of uncertainty. Here we mean actual volatility, volatilities such as implied volatility, cross-sectional dispersion of variables (such as stock returns and sales growth), and estimates based on GARCH models. Unconditional volatility models and conditional volatility models are two examples of models that are used in uncertainty measurement. Studies by Blanchard and Simon (2001), Giovannoni and Dois Tena (2008), Ghosal and Ye (2015), and Boeck et al. (2023) are examples of uncertainty measurement based on unconditional volatility models. In conditional volatility models, uncertainty is measured based on the conditional variance of forecast errors. In this method, how to specify the conditional variance is of pivotal importance. GARCH models and Stochastic Volatility (SV) models are two of the commonly applied models to specification conditional variance. By comparing uncertainty measures, Chua et al. (2011) have provided evidence to support the appropriateness of uncertainty measures based on GARCH models. However, there is various evidence for the superiority of SV models over GARCH models (Kastner, 2016). In general, various types of GARCH models have the same estimation method, but there are various methods for estimating the SV models (Bos, 2012). SV models allow conditional volatility to be time-varying, and this variation generates time-varying uncertainty. However, the estimation of SV models involves complex computation. The development and application of methods of simulated moments (MSM), Markov Chain Monte Carlo algorithm (MCMC), and other simulation methods in the estimation of SV models have caused these models to gain an advantage over GARCH models over time. Jurado et al. (2015) have introduced the macroeconomic uncertainty measure as the stochastic volatility of forecast errors in a large number of macroeconomic variables. In this study, the variance of forecast errors is specified in the form of an SV model, and then the parameters of the model are estimated using the MCMC algorithm. Carriero et al. (2018) have measured the macroeconomic uncertainty based on a large Vector Autoregressive model with errors whose SV is driven by common macroeconomic and financial factors. However, Ludvigson et al. (2021) showed that in most of the popular proxies of uncertainty (stock market and other model-based proxies), the volatilities are not generated by the uncertainty flow of the economy. They argue that these proxies erroneously attribute forecastable volatility to the path of uncertainty.

In its most prevalent form, news-based uncertainty is represented by the time series of the number of news articles uncertainty-related. In this context, Baker et al. (2016) have measured the level of uncertainty based on the frequency of uncertainty-related words in newspaper articles and reports by using text search methods. In this approach, the more the number of uncertainty-related words in a certain period, the higher the uncertainty level of that period. Ahir et al. (2022) have constructed the World Uncertainty Index based on text mining the country reports of the Economist Intelligence Unit. In general, although this approach is theoretically less appealing, it can be more attractive in practice (Anzuini & Rossi, 2020).

A review of the literature in the context of uncertainty measurement reveals that researchers have used various proxies to measure economic uncertainty. In some studies, instead of relying on a specific measure, various indicators have been used to measure the level of uncertainty. It is difficult to evaluate various measures of uncertainty because each of these measures has its advantages depending on the application. However, some uncertainty measures suffer from limitations in the computation. For example, survey-based data are only available for a limited number of countries (such as the United States and some EU member countries). Therefore, computing measures based on survey data is impossible for many countries. There are also many limitations regarding measures based on the news. For example, in many countries, there are no independent press and newspapers, or severe limitations are imposed on the press. This problem leads to a significant difference between the real level of uncertainty and the level of uncertainty measured based on the news. In order to evaluate uncertainty measures, some researchers highlight that a measure can be an appropriate proxy for uncertainty that is consistent with the theoretical concept of uncertainty (Jurado et al., 2015; Carriero et al., 2018; Ludvigson et al., 2021). In addition, based on the theoretical literature, the level of uncertainty increases during recessions and economic-political crises. Therefore, another way to evaluate uncertainty proxies is to check their conformity with recessions and economic-political crises. Caldara et al. (2019), Cascaldi-Garcia and Galvao (2019), and Ludvigson et al. (2021) have provided evidence to confirm the correlation between uncertainty and business cycles. Bloom (2014) has referred to time-varying uncertainty. Elsewhere, he has emphasized the relationship between the level of uncertainty and domestic and international political events (Bloom, 2018).

3. Research Method

Uncertainty is inherently unobserved, and there are several ways of characterizing it. Various proxies have been developed to measure uncertainty. Based on the theoretical literature, the uncertainty process has three main features: Firstly, it does not include predictable variations; secondly, it pertains to future events, and thirdly, it is time-varying[1]. Hence, when measuring uncertainty, these characteristics should be considered as much as possible to construct an appropriate proxy for uncertainty. The term "unpredictable" in the operational definition of uncertainty holds particular significance. In a basic definition, Campbell (2007) defines the uncertainty of an economic variable as the unpredictable variations of that variable. In this context, Jurado et al. (2015) and Ludvigson et al. (2021) have measured macroeconomic uncertainty based on a large number of macroeconomic time series. Within this framework, uncertainty is computed for each time series separately (individual uncertainty) based on the conditional variance of the forecast errors (the unpredictable component of the time series). Subsequently, macroeconomic uncertainty is determined by computing the weighted average of individual uncertainties.

The purpose of this study is to compute a proxy of uncertainty that represents the uncertainty of the overall macroeconomic environment. To address these issues, the current study has employed time series models for computing

[1] In general, the behavior of a time-varying system changes over time which means the system's output, over a certain period, depends not only on its present inputs but also on its past inputs and the passage of time. Time variant systems respond differently to the same input at different times. For more information: Hover, F. S., & Triantafyllou, M. (2009) System Design for Uncertainty. Massachusetts of Institute of Technology, *MIT Open Course Ware.*

uncertainty. Our approach is based on the benchmark study conducted by Jurado et al. (2015). In the following section, the econometric framework and the methodology for computing the uncertainty proxy will be explained.

3.1 Econometric Framework

According to Jurado et al. (2015), the computation of the macro uncertainty index includes three stages:

1- At the first stage, it is required to estimate the forecastable component of the time series y_{jt} (as the one series of the large set of time series used) in the h-step-ahead (i.e. $E[y_{jt+h}|I_t]$). For this, should form factors from a large set of predictors $\{X_{it}\}, i = 1, 2, \dots, N$, whose span is as close to I_t as possible. By using these factors $E[y_{jt+h}|I_t]$, can be approximated using a Diffusion Index Forecasting ideal for data-rich environments (first ingredient).

2- At the second stage, the forecasting errors in h-step-ahead are defined as $V_{jt+h}^{y} = y_{jt+h} - E\left[y_{jt+h}|I_t\right]$. In the continuation, this operation requires an estimate of the conditional (based on the information of time t) volatility of these errors, $E\left[\left(V_{jt+h}^{y}\right)^2|I_t\right]$. For this, for both *one*-step-ahead forecast errors in y_{jt} and analogous forecast errors for the factors, a parametric stochastic volatility model has been used. These volatility estimates are used to compute recursively the values of $E\left[\left(V_{jt+h}^{y}\right)^2|I_t\right]$ for $h > 1$. In the next step, the h-period ahead uncertainty in the series y_{it} (individual uncertainty) is computed as the conditional variance of the unpredictable component of the future values of that time series as follows (second ingredient).

$$u_{jt}^{y}(h) = \sqrt{E\left[\left(y_{jt+h} - E\left[y_{jt+h}|I_t\right]\right)^2\right]|I_t} \tag{1}$$

3- At the third stage, macroeconomic uncertainty ($U_t^{y}(h)$) is constructed as a weighted average of aggregating individual uncertainty. For this, by aggregating individual uncertainty of the time series in each period based on the weights that are defined for them (w_j), the macroeconomic uncertainty measure is computed as follows (third ingredient):

$$U_t^{y}(h) = \underset{N_y \to \infty}{\text{Plim}} \sum_{j=1}^{N_y} w_j u_{jt}^{y}(h) = E_w\left[u_{jt}^{y}(h)\right] \tag{2}$$

Jurado et al. (2015) have used the equally-weighted average of individual uncertainties (equation 3) in order to compute the h-period ahead macroeconomic uncertainty measure.

$$\bar{U}_t^{y}(h) = \frac{1}{N_y} \sum_{j=1}^{N_y} \hat{u}_{jt}^{y}(h) \tag{3}$$

In equation (3), $\hat{u}_{jt}^{y}(h)$ indicates the estimated values of individual uncertainties ($u_{jt}^{y}(h)$). This measure does not impose any structure on the individual uncertainties above and is beyond the assumptions on the process of latent volatility.

In this framework, the first step is to select an appropriate predictive model in order to estimate the conditional expectation sentence ($E[y_{jt+h}|I_t]$). Selecting this model is crucial because forecast errors are constructed based on this model, and these errors form the basis of uncertainty measures. To identify a true forecast error, the richness of the predictive model is very important, so the model must be specified in such a way that the constructed forecast error is purged of predictable content. In the framework of standard models, some predetermined conditional variables are selected to predict a variable, and then forecast errors are computed using the estimation of the model. If economic agents (such as financial market participants) have more information than that in the conditional variables, an omitted-information bias may arise in the model. In order to resolve this problem, the forecasting equations should be augmented to prevent the occurrence of omitted information bias. By augmenting conventional forecasting equations with common factors estimated from large data sets, forecasts of both real activities and financial returns are improved. This issue is crucial in measuring uncertainty because discarding the relevant information in the form of forecasts will lead to spurious estimates of uncertainty and its dynamics. To resolve this problem, based on the approach of Bai and Ng (2008) it is possible to use the diffusion index forecasting method, by which a relatively small number of factors estimated from a large set economic time series are augmented to a standard forecasting model. By including these factors, nonlinear functions (square of some factors), and the factors created by the nonlinear transformations of raw data, in the forecasting model, it is possible to resolve the problem of omitted information. This approach eliminates mere reliance on a small number of exogenous predictors and makes it possible to use information in a vast set of economic variables, which (probably) scope the unobservable information sets of economic agents. In what follows, the procedure for estimating these factors is described.

It is assumed that y_{jt} denotes a series that we wish to compute uncertainty and its value in period $h \geq 1$ is estimated from a factor augmented forecasting model in the form of equation (4):

$$y_{jt+1} = \varphi_j^y(L)y_{jt} + \gamma_j^F(L)\hat{F}_t + \gamma_j^W(L)W_t + v_{jt+1}^y \tag{4}$$

The components of equation (4) have autoregressive dynamics, so that $\varphi_j^y(L)$, $\gamma_j^F(L)$, and $\gamma_j^W(L)$ are polynomials of order finite in the lag operator L of orders p_y, p_F, and p_W, and to exert these dynamics are included. The vector $\hat{F}_t$ are consistent estimate of predictor factors and the vector W_t contains additional predictors that are used to augment the predictions in the conditional mean equation. These factors are estimated based on the approach of Bai and Ng (2002) and using the static principal component (PCA) method. Bai and Ng (2006) show that the estimated factors can be treated as though they were observed in the subsequent forecasting regression. The important feature of the regression equation (4) is that the prediction error of y_{jt+1}, each factor $F_{k.t+1}$, and the additional predictor $W_{l.t+1}$, are allowed to have time-varying volatilities, denoted by σ^{y}_{jt+1}, σ^{F}_{kt+1}, σ^{W}_{lt+1}, respectively. This feature generates time-varying uncertainty in the series y_{jt}. In this framework, when the predictor factors have autoregressive dynamics, a more compact representation of equation (4) is the Factor Augmented Vector Autoregression (FAVAR)[1]. As mentioned, the stochastic volatility of forecast errors related to time series and predictor factors generates time-varying uncertainty. The choice of stochastic volatility is important from this point of view, which permits the generation of a shock to the second moment, and this shock is independent of innovations to y_{jt} itself. Whereas GARCH type models lack this feature.

After estimating the predictor factors and determining other characteristics, the regression equation (4) is estimated and the forecasting errors of the time series that we seek to compute their uncertainty are constructed. Since, by default, the predictor factors in the regression equation (4) have autoregressive dynamics, the forecasting errors of the factors will also play a role in computing the uncertainty of the time series. In fact, when h > 1, the future values of predictor factors are unknown, so it is necessary to forecast the future values of these factors. Based on the approach of Bai and Ng (2008), the future values of each predictor is forecasted by an AR(4) model. Following this, the forecast errors of these factors (v^{F}_{jt}) are computed (both $\hat{F}_t$ and W_t). Jurado et al. (2015) showed that in the case that the forecast horizon is $h > 1$, the forecasting error of predictor factors in time t affects the forecast error variance of the series in time $t+h$ and consequently, it will affect the uncertainty of the series[2]. Therefore, the computing of the conditional variance of the forecast error of the time series requires estimates of the stochastic volatility of the forecast error of the series (σ^{y}_{jt+1}) and the stochastic volatility of the forecast error of the predictor factors (σ^{F}_{t} and σ^{W}_{t}). For this purpose, in the framework of the SV model, the logarithm of the forecast error volatility of the series (σ^{y}_{jt+1}), and the predictor factors (σ^{F}_{t}) are specified[3] in the equations (5) and (6), respectively.

$$log\left(\sigma^{y}_{jt+1}\right)^2 = \alpha^{y}_{j} + \beta^{y}_{j} log\left(\sigma^{y}_{jt}\right)^2 + \tau^{y}_{j}\eta_{jt+1}, \;\; \eta_{jt+1} \sim (iid)N(0,1) \tag{5}$$

$$log(\sigma^{F}_{t})^2 = \alpha^{F}_{i} + \beta^{F}_{i} log(\sigma^{F}_{t-1})^2 + \tau^{F}_{i}\eta^{F}_{t}, \;\; \eta^{F}_{t} \sim (iid)N(0,1) \tag{6}$$

[1] For more information about this model, refer to the following source:
Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In *Handbook of macroeconomics*, Vol. 2, pp. 415-525), Elsevier.

[2] For more information, refer to Jurado et al. (2015).

[3] The specification SV of the error of the additional predictors (σ^{W}_{t}) is the same as the specification SV of the error of the predictor factors (σ^{F}_{t}).

In the above equations, α_j, β_j, τ_j and α_i, β_i, τ_i are the SV parameters. To estimate these parameters, we first compute the forecasting errors (v^y_{jt+1}) of equation (4). Additionally, we employ the AR(4) model to estimate the forecast errors of the predicting factors (v^F_t).[1] Subsequently, these parameters are estimated using the MCMC algorithm. The average of these parameters over the MCMC draws is used to compute the conditional variance of forecasting errors (second ingredient). The SV model permits the construction of a shock to the second moment (i.e. η) that is independent of the innovations to the first moment, and consistent with theoretical foundations of uncertainty. After computing the forecast error variance, individual uncertainties for each of the economic time series are computed based on the square root of the h-step-ahead forecast error variance. Finally, macro uncertainty (third ingredient) is computed based on the cross-sectional average (CSA) of individual uncertainties and in the form of equation (3).

4. Empirical Results
4.1 Statistical Dataset

In this study, the dataset used to measure uncertainty includes 72 macroeconomic and institutional time series of Iran's economy. The sample period spans from 1991:Q2 to 2022:Q1. The datasets have been classified into 9 groups. This classification is based on the economic nature of the variables. Table (1) describes a summary of dataset structure.

Table 1. Summary of dataset

Groups	Details	Number of Series (N)
Real activities	Aggregate added value	12
Expenditures	Expenditures of different sectors	9
Monetary and credit	Monetary and credit variables	19
Government budget and fiscal position	Government revenues and expenditure	4
Price indices	CPI and their components, WPI and their components, and construction services index	6
Financial assets and capital market	Stock market indices and price of gold coins	2
Exchange rate	Exchange rate, and real and nominal effective exchange rates	5
Energy sector	Energy consumption and oil price	6
Institutional variables	Institutional indices	9

Source: *developed by authors*

Since the aim of the present study is to estimate the uncertainty index at the aggregate level of Iran's economy, it has attempted to include all sectors of macroeconomics in the uncertainty modeling. Furthermore, the institutional

[1] Where $v^y_{jt+1} = \sigma^y_{jt+1}\varepsilon^y_{jt+1}$ $with$ $\varepsilon^y_{jt+1} \sim (iid)N(0,1)$ and $v^F_t = \sigma^F_t \varepsilon^F_t$ $with$ $\varepsilon^F_t \sim (iid)N(0,1)$

structure of the economy is one of the pivotal factors influencing uncertainty. In the theoretical literature of uncertainty, institutions play a prominent role to the extent that the institutional structure of an economy can substantially contribute to controlling and decreasing the level of prevailing uncertainty in the economy. In previous studies conducted in the context of measuring uncertainty, this issue has been overlooked. Therefore, to fill this gap in the present study, a vector of institutional variables has been included in uncertainty modeling. A collection of time series for each group of variables and their data sources is detailed in Table (2) (Appendix (1)). As shown in Table (2), a set of 72 macroeconomic and institutional variables (comprising 63 macroeconomic time series and 9 institutional time series) has been employed for measuring economic uncertainty. Considering the seasonal nature of the time series, the raw data were initially seasonally adjusted using the X-13 filter. In the next step, the raw data have been transformed into stationary data through suitable transformations. The details of the data transformations are explained in Appendix (2).

4.2 Estimation of Factors and Forecast Errors

Estimating equation (4) and computing forecast errors require extracting predictor factors ($\hat{F}_t = \left(\hat{F}_{1t}, \dots, \hat{F}_{r_F t}\right)^{\prime}$) and additional predictors (W_t). These factors are estimated using the static principal component analysis (PCA), following the framework developed by Bai and Ng (2002). According to this approach, static factors (F_t) in a large $N \times T$ environment are estimated using the asymptotic principal component method. The matrix $T \times r_F$ estimated factors ($\hat{F}_t$) is $\sqrt{T}$ times the r_F eigenvectors corresponding to the r_F largest eigenvalues of the $T \times T$ matrix $X\acute{X}/(TN)$ in decreasing order with $\hat{F}'_t \hat{F}_t = I_{r_F}$.[1] Before estimating the factors, the data have been standardized. The results indicate that the vector $\hat{F}_t$ encompasses five predictor factors ($r_F = 5$) estimated from the observations matrix.[2] Loading these factors on the time series showed that among the series, the first factor with Gross Domestic Product, the second factor with sight deposits, the third factor with the Wholesale Price Index, the fourth factor with oil prices, and the fifth factor with the Corruption Index, correlates most heavily. These series are commonly referred to as key series because they play a key role in forecasting variations of the time series. Additionally, three predictor factors are estimated from the squared observations matrix (X_{it}^2). The estimated factors from the squared observations are represented by the vector $\hat{G}_t = \left(\hat{G}_{1t}, \dots, \hat{G}_{r_G t}\right)^{\prime}$. Finally, the additional predictor vector (W_t) encompasses two elements ($r_W = 2$). The first element of W_t is the square of the first factor from the $\hat{F}_t$ vector ($\hat{F}_{1t}^2$), and the second element is the first factor estimated from the square of observations

[1] Here, N represents the number of time series, T represents the number of time series observations, r_F represents the number of the estimated factors, $\hat{F}_t$ represents the vector of estimated factors, X represents the observations matrix ($N \times T$), and I represents the identity matrix.

[2] For more information, refer to Bai and Ng (2002).

($\hat{G}_{1t}$). These quadratic elements in w are used to mitigate against the potential nonlinearities and any possible effect that conditional volatility may impose on the conditional mean function. In the next step, following the Bai and Ng (2008) approach, among these factors, those factors that can provide significant predictions are included in the forecast equation of y_{jt+1}. For this, based on the hard threshold rules, if the absolute value of the computed t-statistic for each factor is greater than 2.575 (1% significance level) that factor is retained as a regressor in equation (4). The next step in estimating equation (4) involves determining the number of lags for time series (p_y), the number of lags for predictor factors (p_F), and the number of additional predictor lags (p_w). The number of these lags has been determined based on the Bayesian Information Criterion[1]. Then, equation (4) is estimated using the least squares method, and sample error sentences (V_{jt+1}^{y}) are extracted. Following this, the SV of these errors needs to be computed. In addition, the SV of the forecast errors of predictor factors also contributes to *h*-period ahead uncertainty in the time series y_{jt} when $h > 1$. Therefore, it is necessary to extract the forecast errors of these factors, and their SV needs to be computed. In this study to predict future values of F_t and W_t, following Jurado et al. (2015), the dynamics of these predictors are specified by an AR(4) model. Then, the forecast errors related to the predictive factors are extracted by estimating this model[2].

4.3 Computation of SV of Forecast Errors

Having extracted the forecast errors for both the time series and the predictor factors, the SV of these errors needs to be computed. To do so, the logarithm of the SV of these errors is specified in the form of equations (5) and (6). In the following, the SV parameters related to these equations are estimated by using the MCMC algorithm. The MCMC algorithm was configured with a burn-in period of 50,000 iterations, and the number of draws was set to 50,000 for subsequent analysis. The increase in the number of iterations enhances the probability of convergence in the chain. By running the MCMC algorithm SV parameters are estimated.[3] We use the averages of these parameters to compute the individual uncertainties. After computing the parameters, the convergence of the Markov chain was assessed using the Geweke statistical test. The results of this test

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[1]Based on Bai and Ng (2008) approach, maximum of the number of lags are set as $p_y = 4$, $p_F = 2$, and $p_W = 2$ (due to the limitation of sample size and preventing the loss of observations).

[2] All computations related to this section, including the estimation of predictor factors, the computation of forecast errors for time series, and the computation of forecast errors for predictor factors, were performed in the MATLAB software environment. The estimation of factors was conducted using the MATLAB software codes developed by Bai and Ng (2008). The computation of forecast errors was also carried out using the MATLAB software codes provided by Jurado et al. (2015).

[3] Since thinning the Markov chain is often advantageous when dealing with a large chain — meaning the number of draws is much greater than the number of burn-in iterations — and there is no need to collect every point from the chain for sampling from the posterior distribution. However, in the present study, where the number of burn-in steps and draws is equal, each point from the chain is used as a sample for parameter estimation, rendering the removal of additional points unnecessary.

indicated that convergence occurs for both estimates (forecast errors of time series and errors of predictor factors)[1].

4.4 Compute the Economic Uncertainty Measure

In the previous stage, we computed the SV of forecast errors. At this stage, we compute individual uncertainties for each of the 72 macroeconomic and institutional time series[2]. As denoted in equation (1), the *h*-period ahead uncertainty in the variable y_{jt} is defined as the square root of the forecast error variance. After computing individual uncertainties for each of the time series, this study characterizes *h*-period ahead economic uncertainty as the Cross-Sectional Average (CSA) of individual uncertainties. In the CSA approach, the algebraic value of individual uncertainty determines its weight and importance in the economic uncertainty measure. Figure (1) plots economic uncertainty in Iran over time for two horizons: *h* = 1, and 4 quarters. Figure (1) shows that economic uncertainty in Iran is countercyclical: The correlation of this measure with real GDP growth is -0.61 for *h* = 1. In Figure (1), the solid curve (blue) represents the economic uncertainty for one future quarter (*h* = 1), and the dashed curve (red) illustrates the overall uncertainty for four future quarters (*h* = 4). While the level of uncertainty measure tends to increase on average with *h*, the variability of uncertainty measure decreases because the forecast converges to the unconditional mean as the forecast horizon tends to infinity. The kernel density estimation of these horizons displayed on the left side of the graph, also shows that the kernel density of these two horizons is rather similar, with the difference that the skewness is reduced at *h = 4* (decrease of variability).

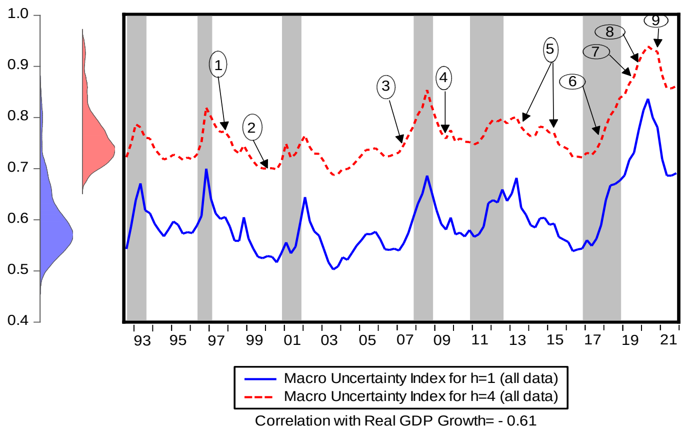

Figure 1. Economic Uncertainty Measure for Iran (CSA Approach)
Source: *developed by authors*

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[1] computations for this section have been conducted in the R environment using the Stochvol package developed by Kastner (2016).
[2] The computations of this section were performed in the MATLAB software environment using software codes provided by Jurado et al. (2015) and Ludvigson et al. (2021).

Notes**:** The data are quarterly and span the period 1992:Q4-2022:Q1. We have collected data since 1991:Q2. However, 2 observations have been lost in the data transformation step, and 4 observations in the computation of the forecast errors of the predictor factors (through the AR(4) process). The data for the economic uncertainty measure presented in Figure (1) is provided in Appendix (3) for reference and further analysis.

Figure (1) plots the economic uncertainty measure for the Iranian economy, computed from the average individual uncertainties of 72 time series related to macroeconomic and institutional aspects. Our assessments indicate that factors within vector $\hat{F}_t$ collectively explain 61 percent of the variations in the entire sample[1]. To evaluate the dynamics of the estimated uncertainty measure, it is necessary to examine its alignment with economic and political events in the Iranian economy over the study period. One approach to assessing uncertainty dynamics is to investigate the behavior of the uncertainty measure during recessionary periods. Bernanke (1983), Bloom (2009), Jurado et al. (2015), and Ludvigson et al. (2021) have presented evidence that the level of uncertainty increases during recessionary periods. Furthermore, the longer the duration of the recessionary period, the notably higher the level of uncertainty would be. In this regard, it is necessary to identify the recessionary periods of the Iranian economy within the period under investigation. For this, initially, the cyclical component of real GDP has been extracted using the Hodrick-Prescott filter[2]. Subsequently, we have identified the peaks to troughs points in the cyclical component graph as recessionary periods. This selection is made because, during recessions, the cyclical component of GDP takes a downward trend. Recessionary periods in Figure (1) are highlighted with a gray background. The findings suggest that during recessionary periods, the level of uncertainty in the Iranian economy has been high. Moreover, in prolonged recessionary periods, we experienced a marked increase in the uncertainty level in the Iranian economy (for instance, from 2008:1 to 2009:1, 2011:1 to 2012:4, and 2017:1 to 2019:1). Uncertainty at the macroeconomic level is also susceptible to political and social events. For instance, evidence from studies by Bloom (2018) and Grimme and Stockli (2018) supports this claim— political and social events (such as the September 11th attacks, Brexit, and the election of Donald Trump as the President of the United States) contributed to an increase in uncertainty. Similarly, some notable political and social events in Iran during the examined period are numbered in Figure (1). These events include: 1) The establishment of the International Center for Dialogue among Civilizations in Iran in 1998; 2) police clash with protesters at Tehran University in 1999; 3) the adoption of the United Nations Security Council resolution against Iran's nuclear program in 2007; 4) Iranian presidential election protests in 2009; 5) initiation of nuclear negotiations in 2013, and the nuclear agreement in 2015; 6) the United States' withdrawal from the nuclear agreement and the resumption of sanctions; 7) Protests and unrests in 2019-2020; 8) The outbreak of the COVID-19 pandemic in Iran in 2020; and finally 9) the lifting of

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[1] This explanatory power is solely related to the vector of predictor factors ($\hat{F}_t$) and has been computed without considering the autoregressive terms and additional predictor factors.

[2] Considering the quarterly nature of the data, the smoothing parameter has been set to 1600.

COVID-19 related restrictions and the import of the COVID-19 vaccine into the Iran. Our findings showed that political and social events with positive consequences (such as cases 1, 5, and 9) led to a reduction in the level of uncertainty measure while events with negative consequences (such as cases 2, 3, 4, 6, 7, and 8) brought about a rise in the level of uncertainty measure in the Iranian economy.

4.5 The Role of Institutional Indicators in Measuring Uncertainty

In this section, we intend to examine the role of institutional indicators as predictor variables for variations in a set of time series and consequently, explore their impact on the algebraic value of the macro uncertainty measure. In general, institutions and institutional structures can impact the level of uncertainty through two main avenues. Firstly, institutions, by defining the choice set for economic agents, create a groundwork for reducing uncertainty. On the other hand, institutions provide the possibility of predicting the behavior of other economic agents. Enhancing the predictive capabilities of economic agents can create a context for reducing uncertainty. From an operational standpoint, this study, which aims to predict variations in economic time series, differs from the use of standard and conventional predictive frameworks (such as conventional Vector Autoregressive models). Instead, it employs an FAVAR model. The key distinction of this model from conventional predictive frameworks lies in the incorporation of predictive factors within the model. From both theoretical and operational perspectives, institutional variables can contribute to a reduction of unpredictable variations and, consequently, decrease the algebraic value of the uncertainty measure. Operationally, this is achieved through changes in predictor factors and enhancing their forecasting capabilities. Essentially, these factors can act as a proxy for the additional information held by economic agents. The primary advantage of the FAVAR model over conventional predictive frameworks lies in its ability to incorporate this additional information. The following explores the role of institutional variables in the computation of uncertainty in the present study. Initially, the uncertainty measure is estimated based solely on the datasets of macroeconomic data, and then its results are compared with the outcomes of the estimated measure based on both macroeconomic and institutional datasets. Our findings reveal that the absence of institutional variables leads to a reduction in the number of predictor factors from 7 to 6. Additionally, the overall explanatory power of the predictor factors significantly decreases. In the presence of institutional variables, these factors collectively explain 61 percent of the variations in 72 time series of macroeconomic and institutional data. However, in the absence of institutional variables, these factors explain collectively 49 percent of the variations in 63 time series of macroeconomic data. Figure (2) plots the estimation results of the economic uncertainty measure based on the CSA approach for the time horizon $h = 1$ for both datasets[1].

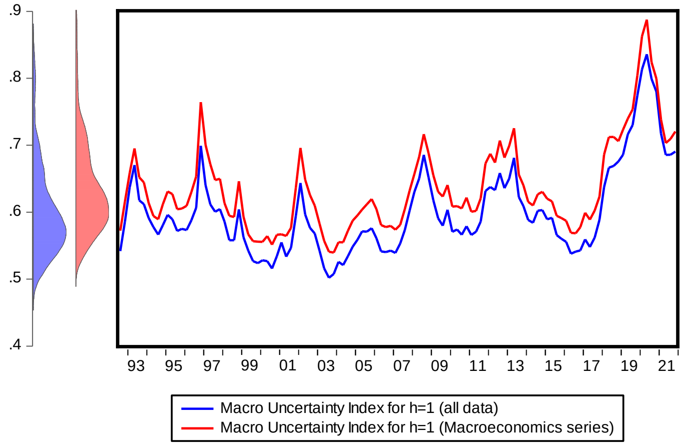

Figure 2. Macroeconomic Uncertainty Measure for Iran (CSA Approach)

Source: *developed by authors*

Notes**:** The data are quarterly and span the period 1992:Q4-2022:Q1. In the computation of the economic uncertainty measure, a dataset consisting of 72 time series has been employed. Out of this total, 63 time series are associated with macroeconomic variables, and 9 time series are related to institutional variables. The blue curve represents the uncertainty measure estimated using the entire dataset, while the red curve signifies the uncertainty measure estimated using the macroeconomic dataset.

Our results clearly indicate that taking into account institutional variables significantly reduces the algebraic value of the uncertainty measure throughout the entire time interval. Additionally, the kernel density curve indicates smoother variations in the index, as the kernel density has decreased in the presence of institutional variables (reduction in skewness). From an operational perspective, the decrease in uncertainty can be attributed to the enhanced predictive capability of predictor factors. As mentioned earlier, these factors, in a sense, represent additional information held by economic agents. Therefore, it can be argued that the inclusion of institutional variables in the system led to improving the predictive capability of predictor factors. Consequently, the magnitude of the forecast accuracy has increased. Ultimately, this has resulted in a diminished numerical value of the uncertainty measure. Despite this, institutions were expected to influence both the numeric level and the direction of uncertainty changes. The high correlation between the two indices could result from various aspects, with the most significant being the use of similar modeling methods for computing each measure.

[1] The results for the time horizon $h = 4$ are consistent with the current findings.

5. Conclusions

Uncertainty is a significant and influential concept in the decision-making process of economic agents. A high level of uncertainty can have adverse impacts on both micro and macroeconomic levels. Given the subjective nature of the uncertainty process, measuring economic uncertainty has encountered various challenges at these scales. Considering the inherent unobservability of economic uncertainty, introducing an objective index for measuring uncertainty seems challenging. Nevertheless, various efforts, especially in recent decades, have been made to introduce a suitable proxy for measuring uncertainty and align it with the theoretical foundations of this stochastic process. Among these, despite the practical appeal of survey-based and news-based uncertainty measures, model-based uncertainty measures have garnered more attention from researchers in recent decades. The reason behind this lies in the greater potential for alignment of these types of measures with the theoretical foundations of uncertainty. The FAVAR model is among the frameworks employed in measuring uncertainty. Its advantage, compared to other models, lies in its ability to provide more accurate predictions of time series through the extraction of latent common factors from the dataset. This enables a more accurate distinction between forecastable and unpredictable components of time series. In fact, the measure of uncertainty should, to the extent possible, be devoid of any predictable content. Therefore, initially, efforts should be made to incorporate factors that enhance better forecasting of time series into the model. One of the fundamental gaps in studies in this context is the sole dependence on economic and financial variables within the operational framework for computing the uncertainty measure. This is despite the fact that the uncertainty process, alongside economic changes, is also influenced by political and social events. To fill this gap, In the present study, the institutional variables have been considered along with the economic and financial variables within the operational framework to measure the uncertainty.

In the present study, a measure of economic uncertainty for Iran was estimated by employing a large number of time series data, encompassing both macroeconomic and institutional indicators. The findings suggest that neglecting institutional factors in the measurement framework can lead to an overestimation of uncertainty. The dynamic assessment of this measure indicates that the level of uncertainty underwent a substantial increase during recessionary periods. In longer recessions, the intensity of this increase in uncertainty was more pronounced. Additionally, the level of uncertainty is influenced by political and social events. Our results revealed that positive political and social events result in a noticeable reduction in the uncertainty measure, while unfavorable political events and social unrest contribute to an increase in the level of uncertainty.

Author Contributions:

All authors have write, read and agreed to the published version of the manuscript.

Funding
This research received no external funding.

Conflicts of Interest:
The authors declare no conflict of interest.

Data Availability Statement:
The data related to the economic uncertainty measure presented in this research is available in Appendix (3) for review and further analysis.

Acknowledgements
Nothing.

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Appendices

Appendix 1. List of time series datasets that are employed for measuring Uncertainty

Table 2. Set of Variables Used in Computing the Uncertainty Measure

Group Name	Variable Name	Transformed Form	Source
Real Activities	Value-added of the Agricultural Sector	Δ ln	1
	Value-added of the Mining Sector	Δ ln	1
	Value-added of the Manufacturing Sector (Including Oil and Gas)	Δ ln	1
	Value-added of the Electricity, Water, and Natural Gas Supply	Δ ln	1
	Value-added of the Construction Sector	Δ ln	1
	Value-added by Wholesale, Retail Trade and Restaurants	Δ ln	1
	Value-added by Transport, Storage and Communication	Δ ln	1
	Value-added of Financial Intermediation Sector	Δ ln	1
	Value-added of Real Estate Sector	Δ ln	1
	Value-added by Health Care	Δ ln	1
	Value-added by Social Service	Δ ln	1
	Gross National Product	Δ ln	1
Expenditures	Private Consumption Expenditure	Δ ln	1
	Public Consumption Expenditure	Δ ln	1
	Gross Capital Fixed Formation	Δ ln	1
	Gross Capital Fixed Formation in Machinery	Δ ln	1
	Gross Capital Fixed Formation in Construction	Δ ln	1
	Net Export of Good and Services	Δ	1
	Export of Good and Services	Δ ln	1
	Import of Good and Services	Δ ln	1
	Investment Expenditure in Housing Sector (Urban)	Δ ln	1

Monetary and Credit	Monetary Base (Source)	$\Delta \ln$	2
	Liquidity (by its Components)	$\Delta \ln$	2
	Money	$\Delta(\Delta \ln)$	2
	Sight Deposit	$\Delta(\Delta \ln)$	2
	Notes and Coin with the Public	$\Delta \ln$	2
	Quasi-Money	$\Delta \ln$	2
	Central Bank Net Foreign Assets	$\Delta \ln$	2
	Central Bank Net Foreign Liabilities	$\Delta \ln$	2
	Central Bank Claims on Public Sector	$\Delta \ln$	2
	Central Bank Claims on Public Corporations and Agencies	$\Delta \ln$	2
	Commercial Banks Claims on Government	$\Delta \ln$	2
	Specialized Banks Claims on Government	$\Delta \ln$	2
	Commercial Banks Claims on Public Corporations and Agencies	Δ	2
	Specialized Banks Claims on Public Corporations and Agencies	Δ	2
	Government Deposits with Central Bank	$\Delta \ln$	2
	Public Corporations and Agencies Deposits with Central Bank	$\Delta \ln$	2
	Government Deposits with Commercial Banks	$\Delta \ln$	2
	Government Deposits with Specialized Banks	$\Delta \ln$	2
	Non-Public Banks and Credit Institutions Claims on Private Sector	$\Delta(\Delta \ln)$	2
Government Budget and Fiscal Position	Oil Revenue	$\Delta \ln$	2
	Tax Revenue	$\Delta \ln$	2
	Current Payments	$\Delta \ln$	2
	Development Payments	$\Delta \ln$	2
Price Indices	CPI- General Index	$\Delta \ln$	2
	CPI- Goods Group	$\Delta \ln$	2
	CPI- Services Group	$\Delta(\Delta \ln)$	2
	WPI- General Index	$\Delta \ln$	2
	WPI- Services Group	$\Delta \ln$	2
	Construct Services Index	$\Delta \ln$	2
Financial Assets and Capital Market	Total Share Price Index (Tehran Stock Exchange)	$\Delta \ln$	3
	The Price of Iranian Bahar Azadi Coin	$\Delta \ln$	2
Exchange Rate	Domestic Currency Per USD (Official Rate- End of Period)	Δ	2

	Domestic Currency Per USD (Official Rate- Period Average)	Δ	2
	Domestic Currency Per USD (Unofficial Rate)	$\Delta \ln$	2
	Nominal Effective Exchange Rate- Trade Partners by CPI	*level*	4
	Real Effective Exchange Rate- Based on CPI	Δ	4
Energy Sector	Energy Consumption	Δ	1
	Spot Price of Iranian Light Crude Oil	Δ	5
	Spot Price of Iranian Heavy Crude Oil	Δ	5
	Spot Price of Oman Crude Oil	Δ	5
	Spot Price of Brent Crude Oil	Δ	5
	Spot Price of West Texas Intermediate Crude Oil	Δ	5
Institutional Variables	Contract Intensive Money (CIM)	Δ	6
	Bureaucracy Quality Index	*level*	7
	Corruption Index	*level*	7
	External Conflict Index	*level*	7
	Internal Conflict Index	*level*	7
	Law and Order Index	*level*	7
	Military in Politics Index	*level*	7
	Government Stability Index	*level*	7
	Socioeconomic Conditions Index	*level*	7

Notes: Each source code in the "Last Column" corresponds to data from a specific source.
- Code 1: Statistical Center of Iran, website: [amar.org.ir]
- Code 2: Central Bank of the Islamic Republic of Iran, website: [cbi.ir]
- Code 3: Tehran Securities Exchange Technology Management Company, website: [tsetmc.com]
- Code 4: International Monetary Fund (IMF), website: [imf.org]
- Code 5: Organization of the Petroleum Exporting Countries (OPEC), website: [opec.org]
- Code 6: Computations Authors
- Code 7: The International Country Risk Guide (ICRG) dataset, website: [prsgroup.com].

Appendix 2. Transformation of raw data

The current study employs the FAVAR framework for forecasting time series. Large-dimensional dynamic factor models are primarily studied in a stationary setting. Therefore, it is necessary to transform raw data into stationary data through an appropriate transformation. This is while economic time series show different characteristics. Some of these series are stationary at the level, while others are non-stationary even at the second-order difference. This complicates the data transformation process. To overcome this challenge, specific functions and algorithms are employed in the *MATLAB* software environment. The aim is to transform each time series into a stationary series, considering their respective natures. For this purpose, seven distinct types of transformations are considered as follows:

Code 1: Stationary Series

Code 2: First-Order Difference
Code 3: Second-Order Difference
Code 4: Logarithm Transformation
Code 5: First-Order Difference of Logarithm (Growth Rate Series)
Code 6: Second-Order Difference of Logarithm (with a Change of Scale)
Code 7: Difference of the Growth Rate Series

The priority of selecting the codes is in the order of 1, 4, 2, 5, 3, 7, 6. For the stationarity test of the time series, has been used Vogelsang and Perron (1998) test. The output of this test is an *Augmented Dickey-Fuller test statistic*, for which the corresponding p-values are computed by Vogelsang (1993). The stationarity of the series before and after each transformation is evaluated using the Augmented Dickey-Fuller test statistic. This is done to ensure the stability of the variables until they become stationary.

Appendix 3. Economic Uncertainty Measure Data

In this appendix, we provide the data associated with the economic uncertainty measure computed for Iran in the study.

	Q1	Q2	Q3	Q4
		1992		
UT_CSA_1	--	--	--	0.54
UT_CSA_4	--	--	--	0.72
		1993		
UT_CSA_1	0.59	0.64	0.67	0.62
UT_CSA_4	0.75	0.79	0.78	0.76
		1994		
UT_CSA_1	0.61	0.59	0.58	0.57
UT_CSA_4	0.76	0.74	0.73	0.72
		1995		
UT_CSA_1	0.58	0.60	0.59	0.57
UT_CSA_4	0.72	0.73	0.72	0.72
		1996		
UT_CSA_1	0.57	0.57	0.59	0.61
UT_CSA_4	0.72	0.72	0.73	0.75
		1997		
UT_CSA_1	0.70	0.64	0.61	0.60
UT_CSA_4	0.82	0.80	0.78	0.77
		1998		
UT_CSA_1	0.60	0.59	0.56	0.56
UT_CSA_4	0.77	0.76	0.74	0.73
		1999		
UT_CSA_1	0.60	0.56	0.54	0.53
UT_CSA_4	0.74	0.73	0.71	0.70
		2000		
UT_CSA_1	0.52	0.53	0.53	0.52
UT_CSA_4	0.70	0.70	0.70	0.70
		2001		

	Q1	Q2	Q3	Q4
		2010		
UT_CSA_1	0.60	0.57	0.57	0.57
UT_CSA_4	0.77	0.75	0.76	0.75
		2011		
UT_CSA_1	0.58	0.57	0.57	0.59
UT_CSA_4	0.75	0.75	0.75	0.76
		2012		
UT_CSA_1	0.63	0.64	0.63	0.66
UT_CSA_4	0.78	0.79	0.79	0.80
		2013		
UT_CSA_1	0.64	0.65	0.68	0.62
UT_CSA_4	0.79	0.80	0.80	0.78
		2014		
UT_CSA_1	0.61	0.59	0.58	0.60
UT_CSA_4	0.77	0.76	0.76	0.78
		2015		
UT_CSA_1	0.60	0.59	0.59	0.57
UT_CSA_4	0.78	0.77	0.77	0.75
		2016		
UT_CSA_1	0.56	0.56	0.54	0.54
UT_CSA_4	0.74	0.74	0.72	0.72
		2017		
UT_CSA_1	0.54	0.56	0.55	0.56
UT_CSA_4	0.72	0.73	0.73	0.74
		2018		
UT_CSA_1	0.59	0.64	0.67	0.67
UT_CSA_4	0.75	0.78	0.80	0.82
		2019		

UT_CSA_1	0.53	0.56	0.53	0.55
UT_CSA_4	0.71	0.75	0.72	0.73
2002				
UT_CSA_1	0.59	0.64	0.60	0.58
UT_CSA_4	0.75	0.76	0.74	0.73
2003				
UT_CSA_1	0.57	0.54	0.52	0.50
UT_CSA_4	0.73	0.71	0.70	0.69
2004				
UT_CSA_1	0.51	0.53	0.52	0.53
UT_CSA_4	0.69	0.70	0.70	0.70
2005				
UT_CSA_1	0.55	0.56	0.57	0.57
UT_CSA_4	0.71	0.72	0.74	0.74
2006				
UT_CSA_1	0.58	0.56	0.54	0.54
UT_CSA_4	0.74	0.73	0.72	0.72
2007				
UT_CSA_1	0.54	0.54	0.55	0.57
UT_CSA_4	0.73	0.73	0.75	0.76
2008				
UT_CSA_1	0.60	0.63	0.65	0.69
UT_CSA_4	0.78	0.80	0.82	0.85
2009				
UT_CSA_1	0.65	0.62	0.59	0.58
UT_CSA_4	0.82	0.79	0.77	0.76

UT_CSA_1	0.68	0.69	0.72	0.73
UT_CSA_4	0.84	0.84	0.87	0.88
2020				
UT_CSA_1	0.77	0.81	0.84	0.80
UT_CSA_4	0.91	0.93	0.94	0.93
2021				
UT_CSA_1	0.78	0.72	0.69	0.69
UT_CSA_4	0.93	0.88	0.86	0.86
2022				
UT_CSA_1	0.69	--	--	--
UT_CSA_4	0.86	--	--	--

Source: *developed by authors*