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RESEARCH PAPER

Measuring Macroeconomic Uncertainty:An Application for Iran

Reza Heybati[a,*]

a. National Competition Center, Tehran, Iran

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Abstract
Given that the Iranian economy is affected by different fluctuations and innovations, it is important to estimate a measure of macroeconomic uncertainty, which represents aggregate level of uncertainty in economics. This study provides a comprehensive time series measure of macroeconomic uncertainty for Iran, estimated separately for different forecast horizons. Moreover, it provides superior econometric estimate of time-varying macro uncertainty, and considers macro uncertainty movements over the period 1991–2015. The estimated measures of macro uncertainty, base-case and its alternatives, show that the important uncertainty episodes of the Iranian economy are associated with deep recessions. Specifically, the major spikes in the baseline estimate occurred during the 1992:1–1994:1, 1994:3–1995:2, and 2011:3-2013:3 recession periods. Finally, results of impulse responses show that the macro uncertainty innovations are followed by a significant persistent decrease in both investment and production, supporting the findings of long-lived negative effects of uncertainty.
Keywords: Macroeconomic Uncertainty, Real Activity, Stochastic Volatility, Forecasting Model, Impulse Responses.
JEL Classification: C38, E17, E32.

Introduction

A large, growing body of literature has recently investigated the measuring time-varying macro uncertainty, and evaluated its role in macroeconomic dynamics (see, e.g., Bloom, 2009; 2012; Fernández-Villaverde et al., 2011; Arellano et al., 2012; Baker et al., 2013; Jurado et al., 2015). This surge in research interest has been driven by several factors. According to Bloom (2014), the jump in uncertainty in 2008 and its likely role in shaping the Great Recession, the increased availability of empirical proxies for measuring uncertainty, and the increase in computing power, which has made it possible to include uncertainty shocks directly in a wide range of models, are more likely to span the important ones.

Iran has experienced large macroeconomic fluctuations over the past three decades. In the presence of such fluctuations, the Iranian macroeconomic environment becomes less predictable or more uncertain. This heightened uncertainty seems to stem from two main sources. First, Iran as an oil-exporting and developing economy is potentially exposed to oil market fluctuations and uncertainties generated by the intrinsic instability of the development process.

Second, Iran has suffered from uncertainties due to its economic and political relationships with other countries, particularly with the US, which has been intensified over Iran's nuclear program, leading to financial and energy sanctions against Iran. These uncertainties have clouded the Iranian economy, making some foreign businesses and investors wary about

* Corresponding author email: r.heybati@gmail.com

economic involvement in Iran, and thereby have had adverse effects on the Iranian trade and investment ties. However, Iran reached an agreement on a framework deal, also known as the “Iran nuclear deal”, with a group of world powers in July 2015, which draws a bright perspective for both its domestic and foreign investors.[1] These conditions, therefore, highlight the importance of measuring macro uncertainty and considering its relationship with real activity in Iran.

In Economics, uncertainty has different types. Due to these varied types and their latent nature, a wide range of empirical measures have been put forth in the literature as a proxy for uncertainty. Regarding the area of application, classification can be considered as macroeconomic uncertainty (Rossi and Sekhposyan, 2015; Jurado et al., 2015; Scotti, 2016), policy-related uncertainty (Pastor and Veronesi, 2013; Born and Pfeifer, 2014; Fernandez-Villaverde et al., 2011; Baker et al., 2016, more recently), economic variables related uncertainty, particularly macro variables like inflation and output growth (Ball and Cecchetti, 1990; Evans, 1991; Grier and Perry, 2000; Fountas and Karanasos, 2007, among many others), or sentiment-related uncertainty (Aarle and Kappler, 2012; Benhabib et al., 2013).

However, the most common measures for evaluating these uncertainties are conditional volatility derived from time series models, particularly GARCH-type and stochastic volatility (SV) models, survey-based measures, realized forecast errors, and a rapidly growing literature on text search methods, e.g., using newspaper coverage frequency. Generally, the concept of uncertainty in economics is related to predictability. It turns out that all common measures of uncertainty, as mentioned above, are in connection with this notion. Thus, according to Cukierman (1984), Ball and Cecchetti (1990), and Jurado et al. (2015), we define h-period ahead uncertainty in a series as the conditional volatility of the purely unforecastable component of the future value of that series.

This paper provides a comprehensive measure of macroeconomic uncertainty, by using mostly aggregated macro series for Iran, and analyzes the dynamic relationship between uncertainty shocks and real activity, by using recursively identified VAR. The paper, therefore, relates to at least two pieces of literature. The first is the research on the measuring and determining proxies for uncertainty, especially the studies which focused on time-varying macro uncertainty. The second is the literature on the effect of uncertainty shocks on economic activity indicators, which generally emphasizes two negative and also two potentially positive effects of uncertainty shocks on economic activity.

The macroeconomic uncertainty index that we propose is constructed in two steps. First, we estimate the uncertainty of macroeconomic variables (individual uncertainties). Then, individual uncertainties are used to obtain an estimate of macro uncertainty. There are alternative ways for each step. That is, there are alternative ways of estimating individual uncertainties and of weighting schemes to get macro uncertainty.

To estimate individual uncertainties, following Jurado et al.'s (2015) approach, we use the factor augmented forecasting model. In this framework, a relatively small number of factors estimated from a large number of economic time series are augmented to standard forecasting models. Jurado et al. (2015) used the method of static principal components to estimate forecasting factors. A fair criticism of the employed factor model, i.e., principal components estimation, is that factors are typically estimated from a large panel of data without taking full advantage of the data structure (Moench et al., 2013).

Therefore, as opposed to Jurado et al. (2015), we use a factor model, which applies common and block-specific factors.[2] As discussed by Moench et al. (2013), the block structure provides a parsimonious way to allow for covariations, which are not sufficiently

1. More recently, substantial concerns have arisen with respect to the deal, when the US withdrew unilaterally from it in May 2018.
2. Kose et al. (2003; 2008), Moench et al. (2013), and Stock and Watson (2010) provide applications of such a model.

pervasive to be treated as common factors. Our proposed uncertainty index, therefore, is based on a hierarchical dynamic factor model, which allows us to estimate a similar comprehensive measure of macro uncertainty using mostly aggregated series. That is, we construct a broad-based measure of macro uncertainty, by using a smaller number of series, achieving dimension reduction and yet explicitly allowing for heterogeneity between blocks.

To obtain macro uncertainty, a simple average of individual uncertainties is used in the base-case implementation. In addition, we use the alternative ways of aggregating individual uncertainties, and compare them to the baseline measure, indicating that the number and timing of all major spikes in time-varying macro uncertainty, as well as the persistence of uncertainty measures, are very similar.

The studies performed in Iran, to our knowledge, are mostly related to the estimating uncertainty of one variable, such as inflation or exchange rates, by using GARCH models. Our contribution is, therefore, to construct a new comprehensive measure of macro uncertainty, by using a relatively large quarterly dataset.

The estimated measures of macro uncertainty, base-case, and its alternatives show that the important uncertainty episodes of the Iranian economy are associated with deep recessions, as was to be expected. Specifically, based on the baseline estimate, there are three episodes, for which macro uncertainty exceeds the corresponding standard deviation line. These spikes occurred during the 1992:1–1994:1, 1994:3–1995:2, and 2011:3–2013:3 recessions, respectively. Results also suggest that macro uncertainty shocks are followed by a significant, persistent decrease in both investment and production, supporting the findings of long-lived negative effects of uncertainty.

The remainder of this paper is organized as follows. Section 2 reviews related literature. In Section 3, the econometric framework is described. Section 4 introduces the data and forecasting factors. In Section 5, we present our base-case estimates of common macro uncertainty and evaluate the dynamic relationship between macro uncertainty and macro dynamics. Section 6 describes the robustness of the results to a range of alternative approaches. Finally, Section 7 summarizes the paper and offers some concluding remarks.

Literature Review

This paper is based on at least two pieces of literature. The first is research on the measuring and determining proxies for uncertainty, especially the studies focusing on time-varying macro uncertainty. This literature has thrived in recent years so that a myriad of economic uncertainty measures has emerged according to the different applications of uncertainty in economics. However, these measures relied primarily on proxies or indicators of uncertainty, because of the lack of direct observations on economic uncertainty, in general, and macro uncertainty, in particular.

Several studies focused on measuring macro uncertainty and analyzed the effect of macro uncertainty shocks. The most commonly used measures ranging from the volatility of stock market returns (Romer, 1990; Hassler, 2001; Greasley and Madsen, 2006; Bloom, 2009; Gilchrist et al., 2010), comparing the realized and historical forecast error distributions of real GDP and inflation (Rossi and Sekhposyan, 2015) to the ex-ante disagreement and ex-post forecast errors using survey expectations (Bachmann et al., 2013), real-time uncertainty about the state of the economy as the squared surprises from a set of indicators (Scotti, 2016), and the common variability in the purely unforecastable component of the future value of a large number of series (Jurado et al., 2015).

Second, there is literature on the effect of uncertainty shocks on economic activity. The theoretical work on this topic dates at least to Bernanke (1983), who built on the theory of irreversible choice under uncertainty to explain cyclical investment. The second literature can be considered in two main channels: “real options” and “risk premium” effects.

The real options effect was introduced by Arrow (1968), Cukierman (1980), and Bernanke (1983), and then extended by Brennan and Eduardo (1985), McDonald and Daniel (1986), and Pindyck (1988), among others. It has been recently re-motivated by Bloom (2009). The idea is that in an uncertain economic condition, in which agents are uncertain about making irreversible, costly decisions on investment, employment, and buying durable goods, it is better off waiting for more predictable conditions. In other words, the option value of delay for the agents is high, when the uncertainty is high.

The risk premium effect highlights the interaction between uncertainty and financial frictions. As Bloom (2014) noted, investors want to be compensated for higher risk, and since greater uncertainty leads to increasing risk premia, this should raise the cost of finance. Furthermore, uncertainty also increases the probability of default, by expanding the size of the left-tail default outcomes, raising the default premium and the aggregate deadweight cost of bankruptcy.[1]

The second strand of theories has raised the possibility that some forms of uncertainty can potentially increase growth. These are the "Oi–Hartman–Abel" effect (after Oi, 1961; Hartman, 1972; Abel, 1983) and the "growth options" argument (see, e.g., Bar-Ilan and Strange, 1996; Segal et al., 2013). However, the second strand is less supported by the empirical evidence, so that the Oi–Hartman–Abel effect requires the ability of firms to easily expand or contract in response to good and bad outcomes, but usually applies to firms with low adjustment costs (Caballero and Leahy, 1996). Similarly, growth options are particularly important for research and development–intensive firms (Kraft et al., 2013), and are often invoked to explain certain periods like the dot-com boom of the late 1990s.

In his seminal work, Bloom (2009) offers a structural framework to analyze the effect of uncertainty shocks. He built and estimated a parameterized model using firm-level data, and simulated a macro uncertainty shock, which produced a rapid drop and rebound in aggregate output and employment. He simulated the effect of the uncertainty shock, showing a good match in both magnitude and timing when is compared to vector autoregression estimations on actual data. In another influential work for the US, Jurado et al. (2015), by using a data-rich environment, provided a new comprehensive time-series measure of macroeconomic uncertainty. They combined 132 mostly macroeconomic series and 147 financial time series into one large macroeconomic dataset. However, they estimated the macroeconomic uncertainty from the individual uncertainties in the 132 macro series only, which included several financial indicators. To estimate the forecasting factors, they employed the criterion of Bai and Ng (2002). Their measures of macro uncertainty fluctuated in a manner, which was often quite distinctive from popular proxies for uncertainty, so that quantitatively important uncertainty episodes appeared far more infrequently.

One of the key facts, which is emphasized in the literature on macroeconomic volatility and development, is that volatility (and therefore uncertainty) is higher in developing countries.[2] Developing countries tend to have the most volatile GDP growth rates, stock markets, and exchange rates. Bloom (2014) examined a panel of 60 countries with available growth and financial data and showed that those with low incomes (less than $10,000 GDP per capita) had 50% higher volatility of growth rates, 12% higher stock-market volatility, and 35% higher bond-market volatility. He concludes, overall, developing countries experience about one-third higher macro uncertainty. Loayza et al. (2007) and Koren and Tenereyo (2007) studied the major mechanisms through which higher uncertainty in developing countries is generated.

1. Other mechanisms related to risk premia are confidence effect and precautionary saving. The confidence effect of uncertainty relates to the models, in which agents have pessimistic (Hansen et al., 1999; Ilut and Schneider, 2011) or optimistic beliefs (Malmendier and Tate, 2005).
2. See, e.g., Loayza et al. (2007) and Bloom (2014).

Iran, as an oil-exporting and developing economy, potentially exposed to oil market fluctuations and uncertainties generated by the intrinsic instability of the development process, has experienced large macroeconomic fluctuations over the past three decades. Esfahani et al. (2012), by using an error-correcting macro-econometric model, pointed to the certain inefficiencies in the demand management of the economy that manifest themselves as negative long-run effects of inflation on real output and investment. Farzanegan and Markwardt (2009) indicated that oil price fluctuations have significant effects on industrial production, inflation, and effective exchange rate.[1]

In addition to the generated uncertainties for Iran as a developing and oil-exporting economy, it suffered from uncertainties due to its economic and political relationships with other countries, particularly with the US. Iran has long been subject to US economic sanctions and recently to the United Nations sanctions over its nuclear program. These uncertainties have clouded the Iranian economy, making some foreign business and investors wary about economic involvement in Iran, so that they have withdrawn from development projects in Iran such as in the oil and gas, shipping, and automotive industries.

The studies conducted in Iran, to our knowledge, have mostly estimated the uncertainty of one variable such as inflation or exchange rates using GARCH-type models. Our contribution is, therefore, to construct a new comprehensive measure of macro uncertainty, by using a relatively large quarterly macro dataset. We will also assess the dynamic relationship between macro uncertainty innovations and real activity dynamics. In addition, the robustness of the baseline estimate of macro uncertainty and the VAR results to alternative approaches and assumptions will be studied.

Econometric Framework

The macroeconomic uncertainty index we propose is constructed in two steps. First, we estimate uncertainty of macroeconomic variables (henceforth "individual uncertainties"). Then, individual uncertainties are used to obtain an estimate of macro uncertainty.

To estimate the individual uncertainties, a factor augmented forecasting model is used. In this framework, by augmenting best-fitting conventional forecasting equations with common predictors estimated from large datasets, we distinguish between uncertainty in a series y_{jt} and its conditional volatility. The difference between the two notions comes from the conditional mean equation. Indeed, the proper measurement of uncertainty requires including available information as much as possible in the conditional mean equation to control for the forecastable variations. So, we use the method of diffusion index forecasting. The premise is that for forecasting purposes, the information in a large number of macroeconomic and/or financial series can be replaced by a handful of forecasting factors.[2]

Hence, following Cukierman (1984), Ball and Cecchetti (1990), and more recently Jurado et al. (2015), h-period ahead uncertainty in series y_{jt}, $y_{jt} \in Y_t = (y_{1t},\dots, y_{Nt})'$ is defined as the volatility of the purely unforecastable component of the future value of that series, conditional on all information available, which is given by

$$\mathcal{U}_{jt}^{y}(h) \equiv \sqrt{E\left[\left(y_{jt+h} - E\left[y_{jt+h}\middle|I_t\right]\right)^2\middle|I_t\right]} \tag{1}$$

where I_t is information available to economic agents at time t. The conditional

1. In the face of such problems, the Oil Stabilization Fund (OSF), recently named as National Development Fund (NDF), was created in 2001 mostly to store a large part of the oil revenues for financing the capital expenditures, and to smooth economic vulnerabilities associated with oil price fluctuations.
2. See, e.g., Stock and Watson (2002; 2006) and Ludvigson and Ng (2007; 2009).

the expectation in Equation 1 is approximated by a diffusion index forecast, as mentioned above.

More formally, following Jurado et al. (2015), let y_{jt} denote a series, which we wish to compute its uncertainty. The series value in period $h \geq 1$ is estimated from the following factor augmented forecasting model:

$$y_{jt+h} = \phi_j^y(L)y_{jt} + \gamma_j^F(L)\hat{\mathbf{F}}_t + \gamma_j^W(L)\,\mathbf{W}_t + v_{jt+h}^y \tag{2}$$

The first term in Equation 2 depicts autoregressive dynamics in series y_{jt}. The role of forecasting factors (predictors) comes through the second and the third terms, where $\hat{\mathbf{F}}_t$ is a vector of forecasting factors, and $\mathbf{W_t}$ is consist of the additional predictors, which will be described. The coefficients ϕ_j^y, γ_j^F, and γ_j^W are the finite-order polynomials in the lag operator L of the orders p_y, p_F, and p_W, respectively. Unlike Jurado et al. (2015), we form the forecasting factors from a hierarchical dynamic factor model (DFM)[1]. Let n_l denotes the number of variables in block $l = 1, \ldots, B$ and $N = (n_1 + \cdots + n_B)$ be the total number of variables, each with T stationary and standardized time-series observations, $t = 1, \ldots$,T. The hierarchical dynamic factor model (DFM) is given by Equation 3:

$$y_{jt} = \beta_t^c \boldsymbol{f}_t^c + \beta_t^b \boldsymbol{f}_{lt}^b + v_{jt} \tag{3}$$

where y_{jt} is the jth series at time t, $\boldsymbol{f}_t^c$ is the single common (aggregate) factor, which is common across all of the N time-series observations and $\boldsymbol{f}_{lt}^b$ is a vector of block-specific factors, which are specific to the series in each block. The coefficients β_t^c and β_t^b are the corresponding latent factor loadings. Finally, v_{jt} is the series-specific or the idiosyncratic error. The idiosyncratic component and factors, i.e., block-specific and common factors, are assumed to be autoregressive (AR) processes of order p and q with normally distributed, zero mean, and contemporaneously uncorrelated errors.

In our base-case implementation, the elements of the vector $\hat{\mathbf{F}}_t$ are consistent estimates of a rotation of block-specific factors, $\boldsymbol{f}_{lt}^b$, and vector $\mathbf{W}_t$ contains two additional predictors, i.e., the estimated single common factor and its square, which are used to capture possible nonlinearities and any effect that conditional volatility might have on the conditional mean function.

The last term in Equation 2 indicates innovations to the series y_{jt}, where we allow them and shocks to predictors to reveal time-varying stochastic volatility. This feature generates time-varying uncertainty in the series y_{jt}. That is, assuming autoregressive dynamics in series y_{jt}, and predictors, we can specify a parametric stochastic volatility model for one-step-ahead prediction errors of y_{jt+1}, and of each factor F_{kt+1} and additional predictor W_{lt+1}. This means that in addition to directly affect the level of the forecast, the predictors play an important role in time-varying uncertainty.

In technical language, the prediction errors of y_{jt+1} reveal time-varying stochastic volatility, i.e., $v_{jt+1}^y = \sigma_{jt+1}^y \varepsilon_{jt+1}^y$, where log volatility has an autoregressive structure as below:

$$\log(\sigma_{jt+1}^y)^2 = \alpha_j^y + \beta_j^y \log(\sigma_{jt}^y)^2\, \tau_j^y \eta_{jt+1}^y \tag{4}$$

1. Kose et al. (2003; 2008), Moench et al. (2009), and Stock and Watson (2010) provide applications of such a model.

where α_j^y, β_j^y, and τ_j^y are stochastic volatility parameters, ε_{jt+1}^y and η_{jt+1}^y are independent and identically distributed (i.i.d.) normal shocks. As mentioned above, we also allow the shocks to predictors, i.e., $\mathbf{F}_t$ and $\mathbf{W}_t$ vectors, to exhibit dynamics as the Equation 4.

It should be noted that this feature is different from GARCH-type models, where the time-varying volatility follows a deterministic evolution instead of a stochastic evolution. Choosing the stochastic volatility model is important because it allows for a shock to the second moment that is independent of the innovations to y_{jt}, consistent with the theoretical models of uncertainty.

After determining the uncertainty in each series, macroeconomic uncertainty is constructed as a measure of the common (latent) variation in uncertainty fluctuations across many series. As Jurado et al. (2015) noted that this is important because uncertainty-based theories of the business cycle typically require the existence of common (often countercyclical) variations in uncertainty across large numbers of series. This measure of macro uncertainty satisfies our definition of macro uncertainty and could be better to evaluate a growing body of evidence regarding the striking rise in uncertainty during recessions. To obtain this estimate of h period ahead macro uncertainty, a simple average of individual uncertainties is used as in Equation 5:

$$\bar{\mathcal{U}}_t^y(h) = \frac{1}{N_y}\sum_{j=1}^{N_y} \hat{\mathcal{U}}_{jt}^y(h) \tag{5}$$

In Equation 5, $\hat{\mathcal{U}}_{jt}^y$ indicates the estimated value of individual uncertainties, and N_y denotes the number of individual uncertainty series.

Data and Forecasting Factors

We illustrate our model with a factor augmented forecasting analysis of macro dataset in Iran, by using a balanced panel of 60 quarterly time series. The macro series is selected to represent broad categories of Iranian macroeconomics. We arrange the data into seven blocks: production, energy, price indices, money and credit variables, fiscal variables, exchange rates and external trade, and finally series on stock market indices. Our blocks are thus defined using prior information about the structure of the data. The dataset spans the period 1990:2–2015:1. After lags in the factor augmented forecasting model and transformations of the raw data, we construct uncertainty estimates for the period 1991:3–2015:1, or 95 quarterly observations. The latent nature of the factors in Equation 3 precludes the use of common regression methods to estimate the model. Instead, we follow Otrok and Whiteman (1998) and Kose et al. (2003; 2008), who use Bayesian techniques with data augmentation proposed in Tanner and Wong (1987), to estimate the forecasting factors.[1]

Then, following Bai and Ng (2008), a thresholding rule using a conservative t test is employed to ensure that the selected factors have significant incremental predictive power. That is, only those regressors are retained which have a marginal t-statistic greater than 1.96 in the multivariate forecasting regression of y_{jt+1} on the candidate predictors known at time t. Four lags of the dependent variables are always included in the predictive regressions.

1. To normalize the signs and scales of the factors and factor loadings in the Equation 3, we follow a strategy similar to Kose et al. (2003). That is, the loading on the common factor and that on the block factors are restricted based on the arbitrarily representative series. These normalizations do not have any economic content and do not affect any economic inference. Furthermore, to implement Bayesian analysis our choice of prior distributions and their parameter values are similar to those used by Otrok and Whiteman (1998) and Kose et al. (2003).

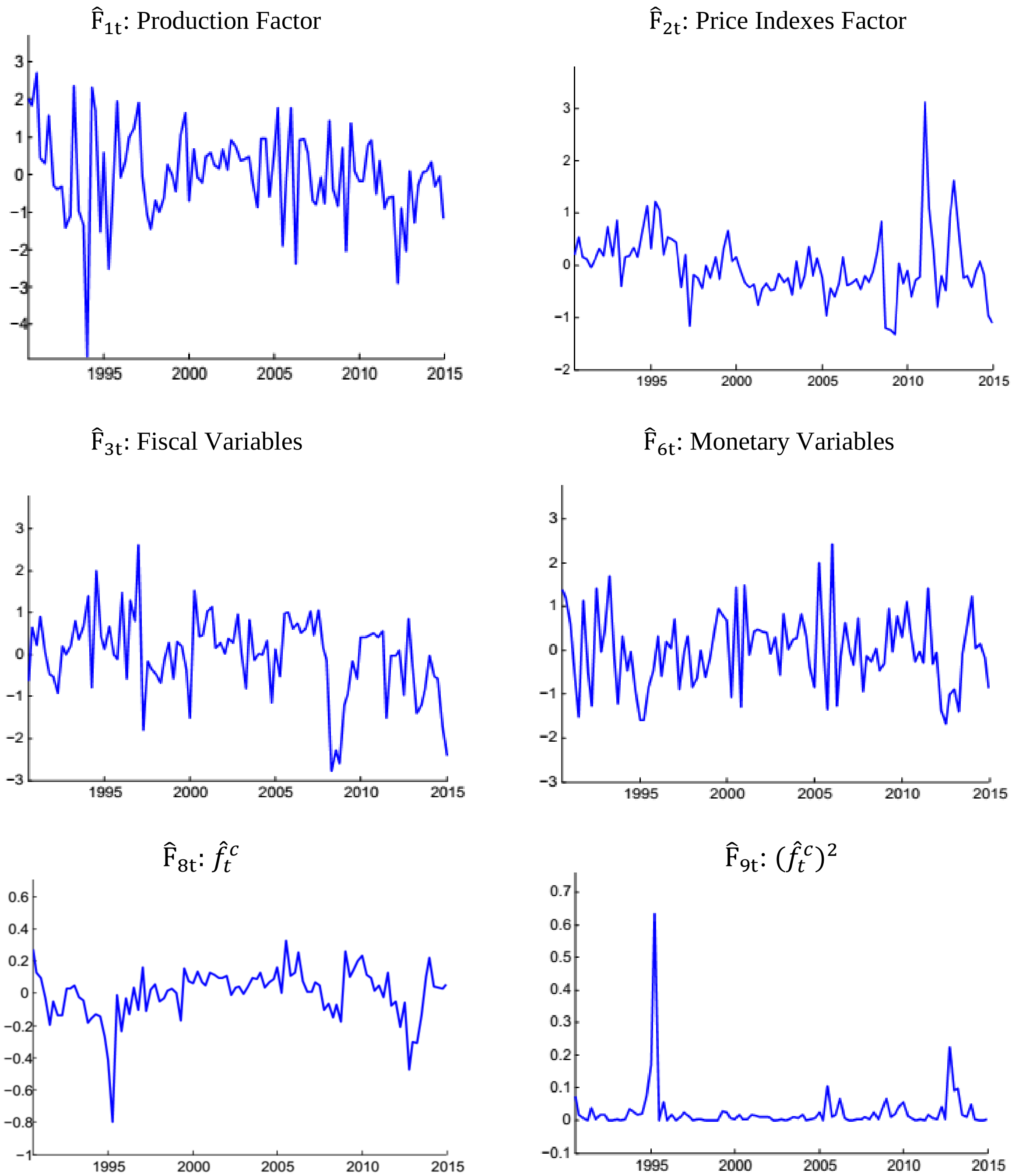

Figure 1. Predictor Factors Based on DFM
Source: Research finding.

Figure 1 plots the block-specific factors, which are frequently chosen as the predictor variables according to the thresholding rule. These are $\hat{F}_{1t}$ (the factor estimated from the production block), $\hat{F}_{2t}$ (the factor estimated from the price indices), $\hat{F}_{3t}$ (the factor estimated from the monetary variables), and $\hat{F}_{6t}$ (the factor estimated from the fiscal variables). The figure also displays the two additional predictors, which are the estimated single common factor, $\hat{\boldsymbol{f}}_t^c$, and its square, $(\hat{\boldsymbol{f}}_t^c)^2$. The 7 block-specific factors explain 56% of the variations in the 60 series, while the single common factor explains on average 11% of the dataset variability.

Empirical Results

To estimate the individual uncertainties $\hat{\mathcal{U}}_{jt}^y(h)$, the posterior mean of stochastic volatility parameters over the Markov Chain Monte Carlo (MCMC) draws are used. The base-case estimates of macro uncertainty $\bar{\mathcal{U}}_t^y(h)$ for different forecasts, horizons are constructed as the cross-sectional average (CSA) of the individual uncertainties, when uncertainty is evaluated once at the mean of the parameters. Instead of the posterior mean, one can also use alternative location statistics of stochastic volatility, e.g., 50^{th} percentiles of the posterior distribution, i.e., posterior median, or its extreme values. There are also alternative ways of estimating individual uncertainties and aggregating these uncertainties to get macro uncertainty.

Before presenting the estimated macro uncertainty, it is worth first identifying recession periods for which the estimated measures are expected to rise dramatically. There is a long intellectual history of the empirical analysis of business cycles. The classical techniques of business cycle analysis were developed by the National Bureau of Economic Research (NBER). These techniques refer to absolute declines in output and other measures. An alternative is to examine cyclical fluctuations in economic time series, which are deviations from their long-run trends. The resulting cyclical fluctuations are referred to as the growth cycles (Stock and Watson, 1999).

Here we adopt the growth cycles method and use linear filters to distinguish between the trend and cyclical components of economic time series, following modern studies of business cycle properties. Specifically, we use the filter of Hodrick and Prescott (1997) to isolate the cyclical component of the real GDP series in Iran.

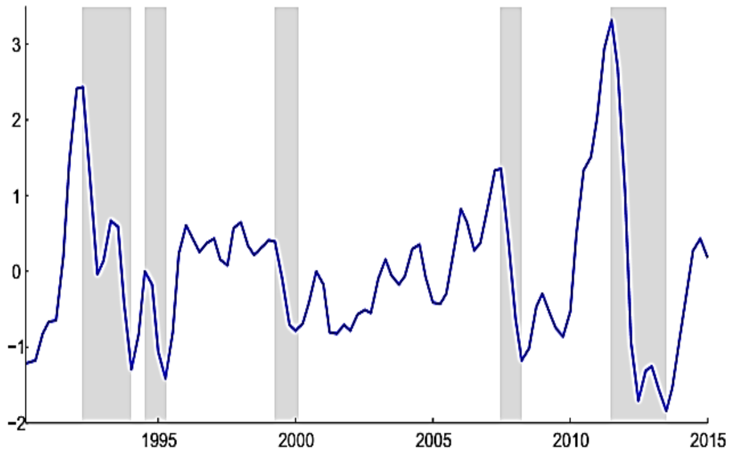

Figure 2. Recession Dates Based on Cyclical Component of Real GDP
Source: Research finding.

Figure 2 plots the cyclical component during 1990:1–2015:1. The cyclical component is obtained after the seasonal adjusting and de-trending with a filter value of $\lambda = 1600$.[1] Gray bars show our identified recession periods, which are determined as 1992:1–1994:1, 1994:3–1995:2, 1999:2–2000:1, 2007:3–2008:2, and finally 2011:3–2013:3. We also applied this procedure to the non-oil GDP series. Results were the same as real GDP series except for a slight difference in the length of a recession period, i.e., 2007:3–2008:2.

Estimates of Macro Uncertainty

Having determined the recession periods, we proceed to construct our measure of macro uncertainty and examine the effect of uncertainty shocks on real economic variables. The estimated time-varying macro uncertainty series $\bar{\mathcal{U}}_t^y(h)$ for the forecast horizon, $h = 1$ (henceforth “baseline estimate”) is plotted by Figure 3.

1. Results are also stable to different de-trending filter values.

Figure 3 shows $\bar{\mathcal{U}}_t^y(1)$ overtime along with identified recession dates. The dashed horizontal line corresponds to 1.65 standard deviations above the mean for the macro uncertainty series. As was to be expected, the main spikes occurred during the deep recessions. Specifically, there are three episodes, in which macro uncertainty exceeds the dashed line.

These spikes have similar magnitudes and occur during the 1992:1–1994:1, 1994:3–1995:2, and 2011:3–2013:3 recession periods, respectively. Nevertheless, the estimated spike of macro uncertainty during 2011:3–2013:3 has been a bit larger, both in terms of persistence and magnitude.

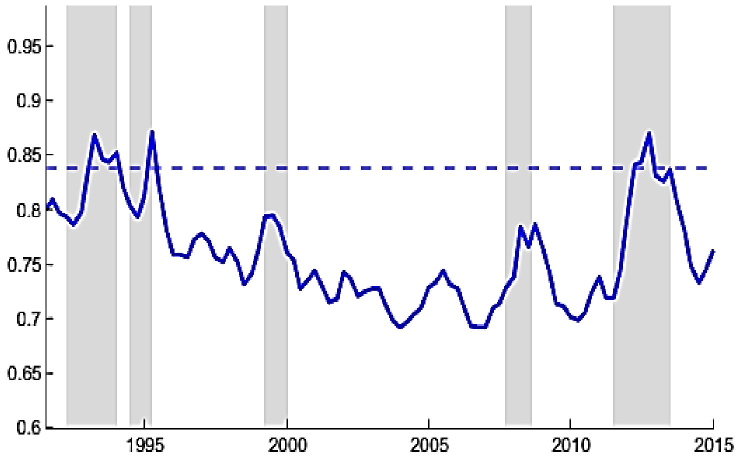

Figure 3. Baseline Estimate of Time-varying Macro Uncertainty
Source: Research finding.

Figure 4 shows the estimated time-varying macro uncertainty for the horizons h = 1, 2, and 4 quarters. Looking across all the uncertainty forecast horizons, we can see that the estimated measures have quite similar dynamics. The dashed horizontal lines have corresponded to 1.65 standard deviations above the mean for each macro uncertainty series. As observed, the level of uncertainties increases with h (on average), while their variability decreases. This is especially true for h = 4 case, where the estimated macro uncertainty exceeds the 1.65 standard deviation line only in two episodes.[1]

Nevertheless, across all horizons, the main spikes in macroeconomic uncertainty again occur in deep recessions, so that the correlation coefficients of $\bar{\mathcal{U}}_t^y(h)$ for the horizons h = 1, 2, and 4 with GDP growth are −0.50%, −0.44%, and −0.42% respectively.[2] The two episodes of a high level of uncertainty in the early 1990s are related to the external debts and balance of payments crisis where they betide during the exchange rate unification and trade liberalizations policies (Pesaran, 2000).

The large spike in the macro uncertainty index in the third episode (2011:3–2013:3) was in connection with energy price liberalization policy and financial and energy sanctions on the Iranian economy were accompanied by rising rates of inflation and free-market exchange rates.

Financial and energy sanctions, which targeted the oil revenues, affected the whole Iranian economy. They increased corruption, rent-seeking, and illegal trade in the country by reducing the inflow of oil revenues and decreasing foreign exchange reserves. They also

1. This arises because the estimated forecast for each series tends to its unconditional mean, and the forecast error variance tends to the unconditional variance as the forecast horizon tends to infinity. For more details, see Jurado et al. (2015).
2. These values for non-oil GDP are −0.43, −0.45, and −0.42, respectively. Of course, these unconditional correlations are uninformative about the causal relationship between uncertainty and real activity.

affected the ability of Iran's central bank to clear the foreign exchange market and maintain the fixed exchange rate. A combination of high demand for strong currencies and their limited supply in the market increased the difference between official and free or black market foreign exchange rates and eventually led to a significant premium (BMP) for major currencies such as the US dollar and the Euro (Farzanegan, 2013).

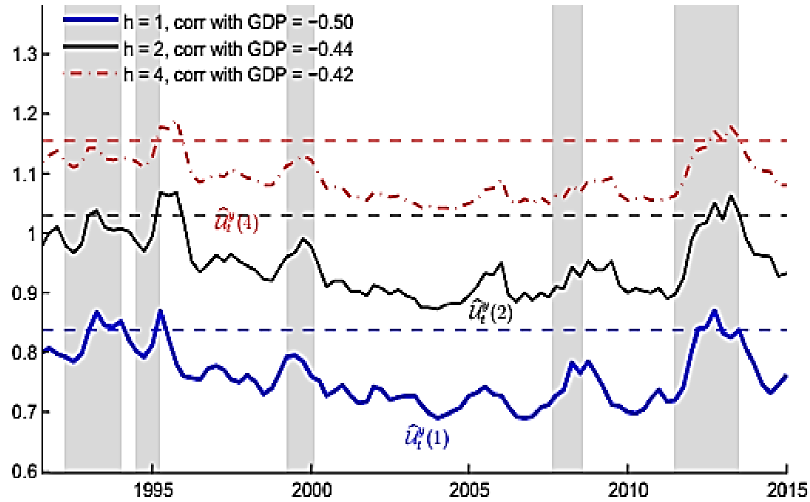

Figure 4. Estimates of Time-varying Macro Uncertainty
Source: Research finding.

Although the increase in macro uncertainty during these episodes is broad-based across individual uncertainties, the three series with the highest uncertainty over the 1992:1–1994:1 period for the baseline estimate are oil value-added, GDP, and a measure of the official exchange rate, i.e., national currency per the US dollar. During the 1994:3–1995:2, the series with the highest uncertainty are nominal free market exchange rate, real free market exchange rate, and GDP. For 2011:3–2013:3, uncertainty is highest for again the real free market exchange rate, nominal free market exchange rate, and government sector debt to the central bank of Iran.

These findings are in line with the historical account of a currency crisis in 1993–1994 and a recession of financial and energy sanctions origin during 2011–2013, which directly affected the foreign exchange market, leading to the second currency crisis in 2011–2012.

Moreover, by comparing macro uncertainty with individual uncertainties, we can analyze to what extent the individual uncertainties are influenced by macro uncertainty and idiosyncratic uncertainty shocks. It shows the relative importance of macro uncertainty in the total uncertainty shocks or the extent to which individual uncertainties are correlated with macro uncertainty. To do this, we estimated the coefficient from a regression of individual uncertainties on macro uncertainty for each series and computed the fraction of variation in individual uncertainties explained by macro uncertainty– the procedure which is used by Jurado et al. (2015).

Alternatively, we can simply compute the correlation coefficients between macro uncertainty and individual uncertainties. Using this process, three series turned out to be highly correlated with macro uncertainty for the horizon h = 1: real exchange rate, nominal exchange rate, and GDP series, with the correlation coefficients equal to 0.53, 0.47, and 0.42, respectively. These series for h = 4 cases are total government expenditure, real exchange rate, and nominal exchange rate, with the correlation coefficients equal to 0.61, 0.60, and 0.57, respectively.

These findings, on the whole, tell us two things. First, the occurrence of the main spikes of macroeconomic uncertainty in deep recessions is in line with the stylized fact that nearly all measures of macro uncertainty rise steeply in recessions. Yet, the estimated macro uncertainty is an aggregate measure of uncertainty, consisting of real activity uncertainty, price uncertainty, economic policy uncertainty, and financial uncertainty. Thus, it seems that the increased macro uncertainty during the recessions not only arises from the real activity uncertainty but also the whole categories of uncertainties.

Second, according to our calculations, the highly correlated series with macro uncertainty are the exchange rate and government expenditure uncertainties for horizons h = 1 and 4, respectively. That is, these series have the highest co-movements with macro uncertainty, and account for a large share in shaping macro uncertainty dynamics. Furthermore, the exchange rate uncertainty has the highest level of uncertainty over the three periods with critical spikes in baseline macro uncertainty. As a result, it is conceivable that exchange rate uncertainty and government expenditure uncertainty play a crucial role in shaping macro uncertainty shocks in Iran.

Macro Uncertainty and Economic Activity

To investigate whether time-varying macro uncertainty matters for economic outcomes, we examined the impact of uncertainty shocks on real economic variables, by using a standard recursively identified VAR to quarterly data over the entire sample. Despite the challenges in drawing causal inferences from VAR models, they are useful for characterizing dynamic relationships. Our benchmark specification of a VAR comprises five variables. Identification is based on Cholesky decomposition with the following ordering: log stock index, macro uncertainty, inflation rate, log total investment, and log GDP. Since the reliable quarterly data for employment is not available, we use the aggregate investment data. The inflation rate is also computed based on the consumer price index (CPI).

Following the related literature, we order our uncertainty measure before the real activity indicators, but after the stock market index.[1] This ordering is based on the assumption that the shocks influence the uncertainty measure, then the prices, and finally the real activity indicators. Including the stock market levels as the first variable in the VAR ensures that the effect of stock market levels is already controlled for, when looking at the effect of macro uncertainty. Our baseline VAR specification includes four lags of all variables.

Before proceeding with the baseline specification, which is comprised of stationary and non-stationary variables, we examined Sims et al.'s (1990) conditions. The ADF unit root tests and Johansen tests fulfilled Sims et al. (1990) conditions.

Figure 5 depicts the impulse response functions of total investment and GDP to a one standard deviation innovation to macro uncertainty across the three uncertainty forecast horizons. The graphs present the initial impact of the orthogonalized positive macro uncertainty innovation and outline how this shock affects the total production and the investment over the following 30 quarters. The red dashed lines show the 90% confidence bands.

The left column plots the responses of investment to innovation in macro uncertainty. For the forecast horizon $h = 1$, following a surprise increase in macro uncertainty, investment declines around 2.1% on impact, continues to drop for about 9 quarters, and then gradually returns close to its pre-shock path. The response of production to a positive innovation in macro uncertainty, however, displays a much more persistent and prolonged, but smaller drop. The latter is also more unsmoothed after a less sizeable impact decline.

1. See, e.g., Bloom (2009) and Jurado et al. (2015). It should be noted that Jurado et al. (2015) reports the impulse responses from an 11-variable and also an 8-variableVAR model. The former estimate impulse responses similar to that studied by Christiano et al. (2005), and place the measure of uncertainty last in the VAR, while the latter is based on the ordering as in Bloom (2009), which has been used in this study.

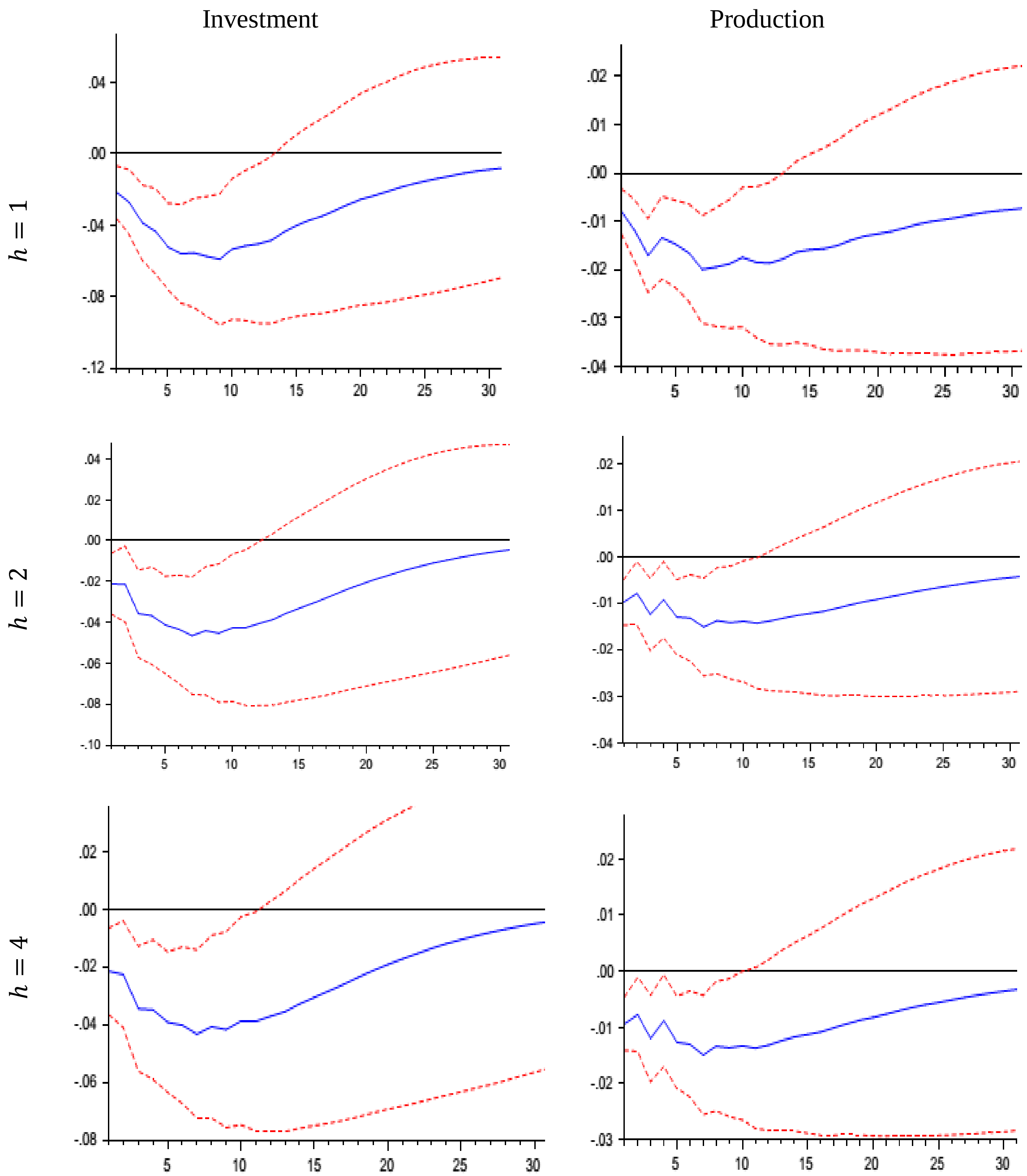

Figure 5. Responses of Investment and Production to Uncertainty Innovation
Source: Research finding.

Therefore, there is no evidence of a strong rebound or overshooting effect in the responses of production, particularly. This figure also shows maximum estimated drops of about 5.9% and 1.9% in investment and production after 9 and 7 quarters, respectively. The observed patterns in the responses of investment and production hold for other horizons, qualitatively, but in smaller magnitudes. These differences in responses of investment and production are in line with the theoretical models, in which investment and hiring decisions are directly influenced by uncertainty shocks. These are channels through which uncertainty affects production and growth.[1]

1. In order to verify the robustness of the VAR results, we provide a variety of alternative specifications and assumptions over variable sets, variable ordering, and lag order which aren't reported here and are available upon request.

On the whole, the responses of investment and production show statistically significant persistent declines followed by subsequent recovery, although different in magnitude, supporting the findings of long-lived negative effects of uncertainty. The persistent and protracted negative responses of real activity are qualitatively similar as compared, for example, with the recent empirical studies by Jurado et al. (2015) and Bachmann et al. (2013) for the US. Yet, the initial declines at the time of the shocks are more sizeable in our case.[1]

Table 1. Decomposition of Variance

Quarters	Variation in investment explained by:			Variation in production explained by:		
	$\bar{\mathcal{U}}_t^y(\mathbf{1})$	$\bar{\mathcal{U}}_t^y(\mathbf{2})$	$\bar{\mathcal{U}}_t^y(\mathbf{4})$	$\bar{\mathcal{U}}_t^y(\mathbf{1})$	$\bar{\mathcal{U}}_t^y(\mathbf{2})$	$\bar{\mathcal{U}}_t^y(\mathbf{4})$
1	8.84	8.09	8.37	11.88	16.14	15.78
2	18.29	13.22	14.13	23.95	16.42	16.35
4	37.39	26.26	24.92	44.09	25.68	24.90
8	56.92	37.52	33.89	51.43	31.16	29.82
20	58.49	39.35	33.88	46.57	28.34	24.84

Source: Research finding.

The quantitative importance of uncertainty shocks on macro-dynamics is evaluated in Table1. This table provides the forecast error variance decomposition for the investment and production. Shocks to $\bar{\mathcal{U}}_t^y(1)$, for example, are associated with 58% of the forecast error variance in investment, and 46% of the forecast error variance in production within 5 years after the shock. These values for $\bar{\mathcal{U}}_t^y(4)$ shocks are around 34% and 25%, respectively. As can be seen, uncertainty shocks can explain the noticeable fraction of the forecast error variance in real activity. In addition, variations in investment, explained by macro uncertainty shocks, are larger than corresponding variations in production.

Robustness of the Results

There are alternative ways of estimating forecasting factors, volatility modeling of individual uncertainties, and of aggregating these uncertainties to get macro uncertainty. As an alternative to our baseline estimate, we estimate forecasting factors by the method of static principal components analysis (PCA) and construct a latent common factor estimate of macro uncertainty based on the first principal component of the covariance matrix of individual uncertainties. As an alternative procedure to univariate volatility modeling, we also use the standard GARCH model. Furthermore, in this section, we examine our baseline uncertainty estimate with stock market volatility as a proxy for macro uncertainty.

Principal Component Estimate

Jurado et al. (2015) employed the method of static principal components to estimate forecasting factors and used a simple cross-sectional average (CSA) to get a baseline measure of macro uncertainty. Based on the same procedure, we estimate a measure of macro uncertainty, by using our macro dataset and compare it with our baseline measure.

As discussed, the potential predictors in the forecasting model in Equation 3 are $\hat{\mathbf{F}}_t = (\hat{\mathrm{F}}_{1t},\ldots,\hat{\mathrm{F}}_{r_F t})'$ and $\mathbf{W}_t$, where in this case the factors are estimated by the method of static principal components. Specifically, $\mathbf{F}_t$ is a vector of latent common factors, and $\mathbf{W}_t$ includes

1. It should be noted that, Jurado et al. (2015) record responses to four standard deviation shocks in macro uncertainty in order that the magnitudes of their response functions were comparable with those of Bloom (2009) VXO shocks. Unlike their estimates, the investment and production responses in our case are based on one standard deviation shock in macro uncertainty.

two additional predictors: squares of the first component of $\hat{\mathbf{F}}_t$, and the first factor formed from the squared observations. The criterion of Bai and Ng (2002) suggests $r_F = 4$ forecasting factors $\mathbf{F}_t$ for the dataset, which explains about 42% of the variations in the 60 series.

There are considerations regarding the estimates of the principal components (PCE) of forecasting factors. Since the criterion is developed under the framework of a large number of series (N) and large time dimensions (T), for a medium or relatively large dataset like our case for which we used mostly aggregate indicators, the estimated factors are more sensitive to the small variation in the N. For example, when we add a few more series related to the stock market, the number of extracted factors increases from 4 to 7, and these factors explain 58% of the variations in the macro dataset. However, the estimated measure of macro uncertainty remains quite similar to the extent that the two series strongly correlated with a correlation coefficient around 0.97.[1]

Moreover, the PCE of forecasting factors does not take into account the full advantage of the data structure, while according to Moench et al. (2013) the block structure provides a parsimonious way to allow for covariations that are not sufficiently pervasive to be treated as common factors. Despite the above considerations, we proceed with the 4 common latent forecasting factors. As before, following Bai and Ng (2008), to ensure that all the selected predictors have significant incremental predictive power, a thresholding rule is employed, by using a conservative t-test.

Figure 6 plots the extracted factors from the macro dataset. These are $\hat{\mathrm{F}}_{1t}$ (highly correlated with measures of real activity, such as total production and industrial value-added.), $\hat{\mathrm{F}}_{2t}$ (loads heavily on stock market returns and the price indices), $\hat{\mathrm{F}}_{3t}$ (highly correlated with measures of fiscal variables), and $\hat{\mathrm{F}}_{4t}$ (highly correlated with oil prices). In addition to the 4 common latent factors, we also include two additional predictors in $\mathbf{W}_t$, that is, the square of the first factor ($\hat{\mathrm{F}}_{1t}^2$) and the first factor formed from the squared observations, $\hat{G}_{1t}$. Four lags of the dependent variable are always included in the predictive regressions.

After identifying the forecasting factors and estimating individual uncertainties based on the same forecasting equations, we construct the alternative measure of macro uncertainty. Instead of a simple cross-sectional average, it is also possible to get macro uncertainty based on PCA. Figure 7 depicts the different estimates of macro uncertainty for forecast horizon *h*=1. In Figure 7, we consider the alternative estimates of forecasting factors and the alternative weighting scheme to get macro uncertainty, as denoted by the first and the second terms, respectively.

1. This implies that the selected factors based on the thresholding rule have similar dynamics for the two estimation processes.

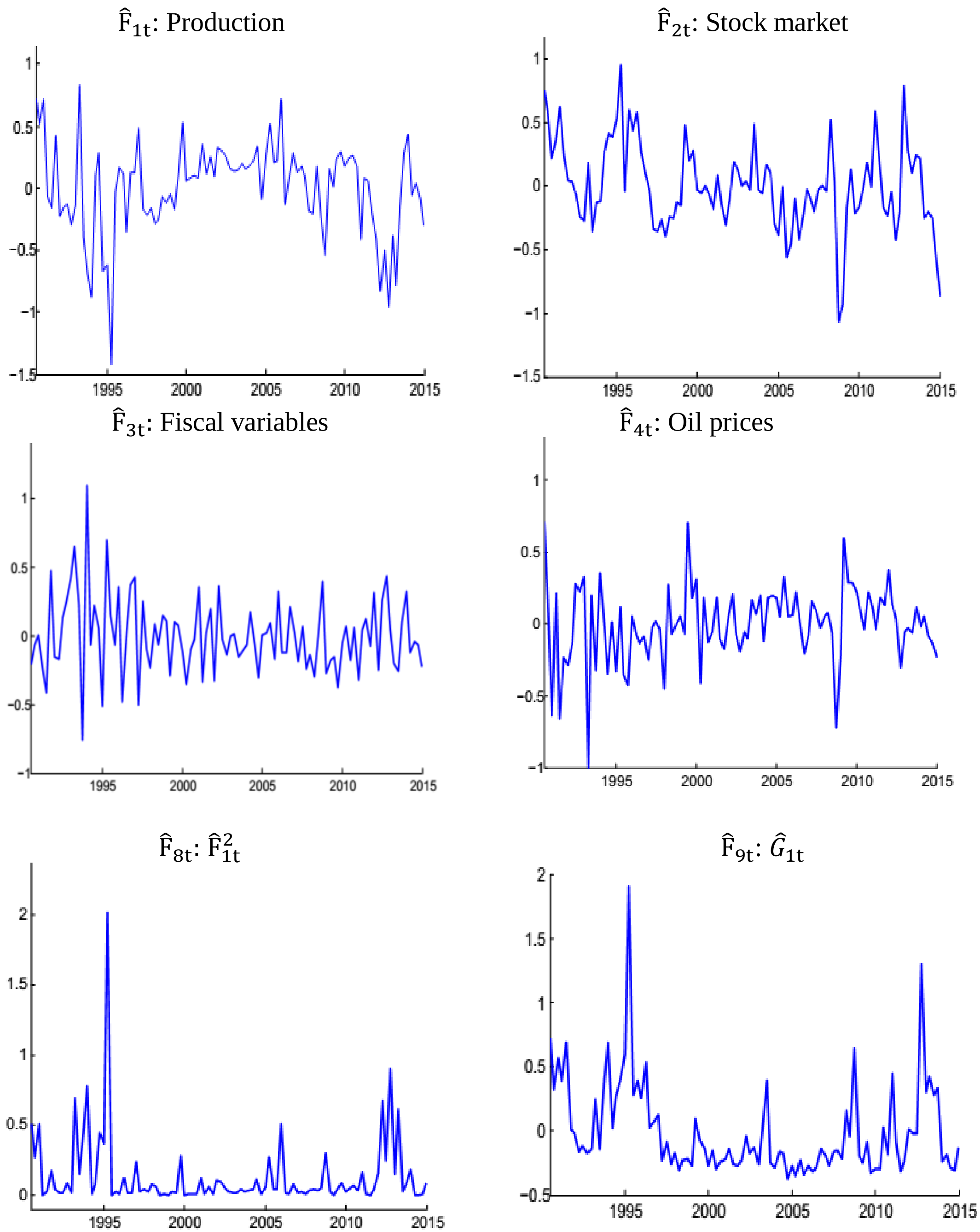

Figure 6. Predictor factors based on PCA
Source: Research finding.

For example, for the baseline estimate, the dynamic factor model (DFM) is used for estimating the forecasting factors, and the cross-sectional average (CSA) is used for aggregating individual uncertainties, which is denoted by DFM-CSA. All these measures are based on the base-case implementation, in which uncertainty is evaluated once at the posterior mean of the parameters. The measures are highly correlated with each other. Particularly, the baseline estimate and DFM-CSA versus the PCA-CSA estimate are virtually indistinguishable and show the highest co-movement with a correlation of 0.97.

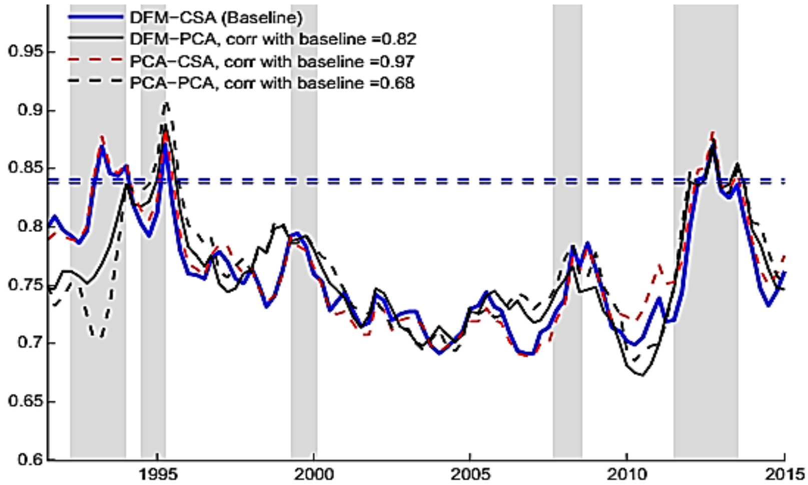

Figure 7. CSA and PCA Estimates of Macro Uncertainty
Source: Research finding.

The two other measures denoted by DFM-PCA and PCA-PCA are the estimates of macroeconomic uncertainty constructed from the first PCA extracted from the entire individual uncertainties.[1] We take the number of common uncertainty factors to be one, which facilitates the comparison with the baseline estimate. According to the first principal components, macro uncertainty spikes around the 1994:3–1995:2 and 2011:3–2013:3 recessions which is in line with the baseline estimate. Notice that the estimated measure based on the first principal component in two episodes exceeds the 1.65 standard deviation line. That is, the difference between the two series is mostly for the 1992:1–1994:1 recession so that the baseline estimate tends to spike more strongly and somewhat before the first principal component series, which comes close to the standard deviation line.

GARCH Estimate

Instead of the stochastic volatility model, one can use the alternative procedures for univariate volatility modelings such as GARCH and the realized volatility paradigms. We consider the standard GARCH(1,1) model developed by Bollerslev (1986), which we simply refer to it as GARCH. When we fit the same mean equation and aggregate in the same way, the estimate of aggregate uncertainty over time is very similar to the baseline stochastic volatility case. The difference in specifications across two series arises from modeling time-varying volatility.

1. To ensure that the latent uncertainty factor is positive, the method of principal components is used to the logarithm of the individual uncertainty estimates.

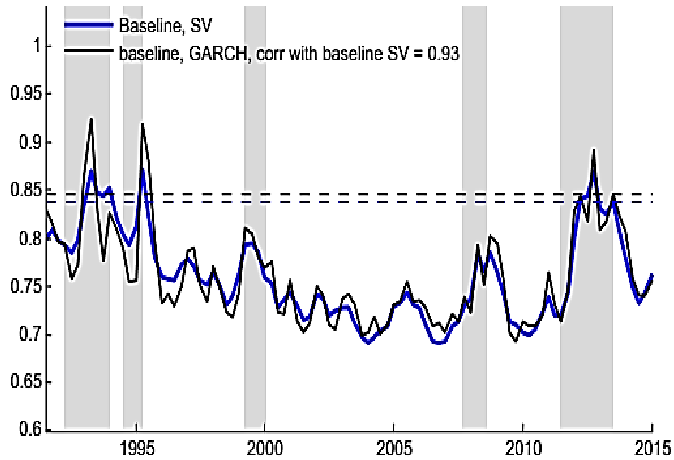

Figure 8. CSA and GARCH Estimates of Macro Uncertainty
Source: Research finding.

As mentioned in Section 3, GARCH-type models are the deterministic volatility models. Nevertheless, volatility follows the stochastic evolution in the stochastic volatility models. The resulting estimates based on the GARCH and the baseline stochastic volatility of macro uncertainty are displayed in Figure 8.

As can be seen, the number and timing of big uncertainty episodes as well as the persistence of uncertainty measure, based on the GARCH estimate, are very similar to the baseline stochastic volatility case. The correlation between the two series is 0.93, displaying a much larger common movement. Nevertheless, the baseline estimate is relatively smoother than the GARCH estimate.

Macro Uncertainty versus Stock Market Volatility

Stock market volatility is the most commonly used proxy for uncertainty (see, e.g., Romer, 1990; Leahy and Whited, 1996; Hassler, 2001; Bloom et al., 2007; Bloom (2009); Gilchrist et al., 2010; Basu and Bundick, 2012). In particular, Bloom (2009) used a measure of stock market volatility based on the VXO Index as a proxy for uncertainty.

In this subsection, we further compare our baseline estimate with stock market volatility as a proxy for uncertainty. It should be noted that the stock market volatility indices like the VIX[1] are not available for Iran. Nevertheless, following Jurado et al. (2015), we use a simple model with a constant conditional mean to estimate stock market volatility. This model, which is most akin to the estimates of implied or realized volatility such as the VIX index, is given by Equation 6:

$$y_{jt+1} = \mu + \tilde{\sigma}_{jt+1}\tilde{\varepsilon}_{jt+1} \tag{6}$$

where y_{jt+1} is the log difference of the stock price index[2], μ is the corresponding constant conditional mean, $\tilde{\sigma}_{jt+1}$ is the corresponding volatility series, where log volatility has an autoregressive structure, and $\tilde{\varepsilon}_{jt+1}$ is independent and identically distributed (i.i.d.) normal shocks as before.

1. The VIX Index is constructed based on the values of a range of call and put options on the S&P 500 Index, while the VXO measures volatility in the S&P 100 Index.
2. We obtain the stock price index series from Tehran Stock Exchange (TSE) database.

Figure 9 compares the resulting estimate of one-step-ahead stock market volatility (SMV) using the above simple model to the baseline estimate. It shows that there are important differences over time in the two series. In particular, there are spikes in stock market volatility that are not present for the baseline estimate, so that a number of the spikes in SVM occur outside of the recessions. Furthermore, with a correlation coefficient of around 0.28, we do not find a strong relationship between the two series.

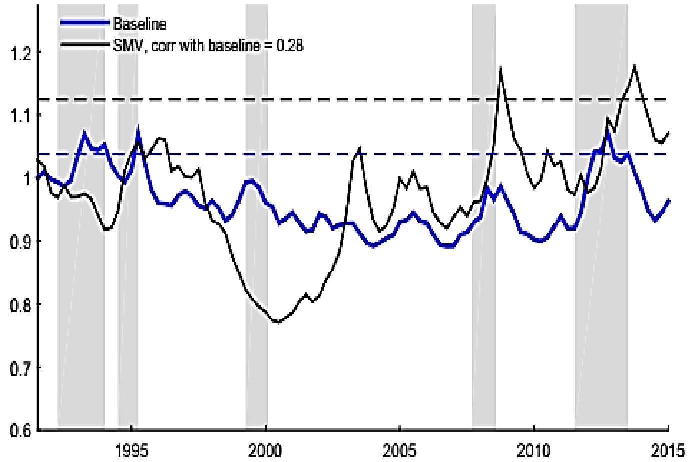

Figure 9. Stock Market Volatility and Baseline Macro Uncertainty
Source: Research finding.

The estimate of SMV based on the simple model in Equation 6 implies that no predictable variation is removed from the stock market series. We further compare the baseline estimate to a case in which forecastable variation in the stock market is removed before computing uncertainty.

This estimate of stock market uncertainty (SMU) using the full set of chosen predictors for the log difference of the stock price index is plotted in Figure 10 along with the baseline uncertainty estimate. As seen again in Figure 10, the two series are positively correlated with a correlation coefficient equal to 0.24. The SMU index is again substantially more volatile than the baseline measure with some sharp peaks that are not correspondingly reflected by the baseline macro uncertainty measure.

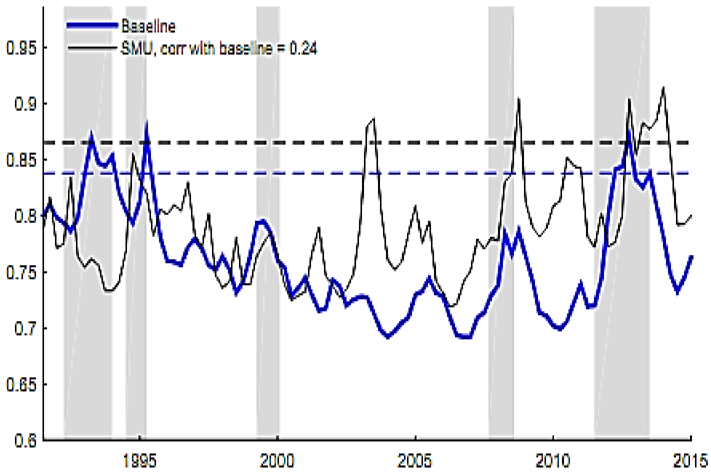

Figure 10. Stock Market Uncertainty and Baseline Macro Uncertainty
Source: Research finding.

Overall, these results show that financial market volatility as measured by the SMV or

SMU is not highly correlated with the baseline measure, especially in terms of the number and timing of the major spikes. Given the relatively underdeveloped nature of the financial market in Iran, it should be unsurprising that there is no close relationship between the financial market volatility and the baseline uncertainty. Although informative, these proxies of macro uncertainty are not comprehensive, and therefore cannot represent a broad-based measure of uncertainty. That is, researchers should be cautious when using financial market volatility as a proxy for macro uncertainty.

Summary and Conclusions

In this study, we introduced a comprehensive measure of macroeconomic uncertainty, and analyzed the dynamic relationship between macro uncertainty and economic activity, by using a relatively large macro dataset in Iran. We estimated individual uncertainties using a factor augmented forecasting model, specifying a parametric stochastic volatility model for prediction errors.

The base-case estimates of macro uncertainty for different forecast horizons were determined as the cross-sectional average of the individual uncertainties. These measures of common variation in individual uncertainties showed that the important uncertainty episodes of Iran over the entire sample were associated with deep economic recessions. Specifically, based on the baseline estimate, there are three episodes for which macro uncertainty exceeds the standard deviation line. These spikes had similar magnitudes and occurred during 1992:1–1994:1, 1994:3–1995:2, and 2011:3–2013:3. Some alternative estimates of macro uncertainty indicated that the number and timing of all major spikes in time-varying macro uncertainty, as well as the persistence of uncertainty, were very similar to the baseline estimate.

Furthermore, by our calculations, among the individual uncertainties, exchange rate and government uncertainties had the highest correlation with macro uncertainty. In particular, exchange rate uncertainty had always existed among the series with the highest level of uncertainty in three major jumps of macro uncertainty. Thus, it is conceivable that exchange rates uncertainty and government expenditure uncertainty play a crucial role in shaping macro uncertainty shocks in Iran. It raises a policy implication based on which conducting efficient policies in the management of exchange rate fluctuations and shrinking government intervention in different markets could mitigate the effects of uncertainty on the economic performance.

To investigate the dynamic causal effects between macro uncertainty and the real economic variables, we used the standard recursively identified VAR model. Results showed that macro uncertainty shocks were followed by persistent protracted negative responses of investment and production, although the responses of production were much smaller. Overall, there is no evidence of a strong rebound or overshooting effect, supporting the findings of long-lived negative effects of uncertainty.

The paper documents an aggregate measure of uncertainty in Iran for the first time. Although there is no study similar to our work, the results are clearly in line with the findings of other countries, especially the US, regarding the increased macro uncertainty during recessions and the persistent negative responses of real activity to innovation in uncertainty.

It should be noted that since our dataset comprises time series on real activity, prices, policy variables, and financial market, the estimated macro uncertainty is a comprehensive measure of macro uncertainty. This aggregate measure is a combination of real, price, policy, and financial uncertainties, which is in line with our definition of macro uncertainty as a measure of the common (latent) variation in uncertainty fluctuations across many series. This point may seem fairly straightforward. However, it should be noted that the most commonly used measures of macro uncertainty use certain series like the volatility of the stock market or GDP growth. Although informative, these proxies of macro uncertainty are not comprehensive, and cannot represent a broad-based measure of uncertainty. However, they can be useful in a non-data-rich environment, particularly if the predictable variation in that series is not to attribute to a movement in uncertainty.

Results showed that the increases in uncertainty were associated with deep recessions. Yet, there is no theoretical consensus on whether the uncertainty is primarily a source of business cycle fluctuations or a consequence of them. Furthermore, a range of questions remains open around the origins of uncertainty shocks and the impact of these shocks, providing a fertile area for future research. To shed light on these questions, it may be useful to distinguish different categories of macro uncertainty and their relative contributions in driving business cycle fluctuations.

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