EJEM
Econ.J.Emerg.Mark.

Economic Journal of Emerging Markets
Available at https://journal.uii.ac.id/jep

Drivers of business cycles in Iran and some selected oil producing countries

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Article Info

Article history:
Received : 26 July 2020
Accepted : 8 March 2021
Published : 1 April 2021

JEL Classification Code:
E32, C34, E37, F44

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DOI: 10.20885/ejem.vol13.iss1.art4

Abstract

Purpose — This study is aimed at analyzing the main drivers of business cycle in Iran and some selected oil producing countries during the 1970:Q1-2015:Q4 period. In addition, the study evaluates causality of leading macroeconomic indicators for each different regimes of the business cycles.

Methods — This study proposes a new methodological approach by combining Markov-Switching Vector Autoregressive (MSVAR) and MS-Granger causality approach.

Findings — The results show that there are diverse sources of business cycle. Iran experienced higher volatility of GDP where machinery investment and export are found as main driver of its business cycle. Meanwhile, consumer price index has countercyclical effect in all countries. We also find some similarities to the US, the UK, and Canada regarding the probability of a business cycle, number of observations, and the average duration, especially in the first regime of MS-VAR models. The high level of oil price volatility relative to the GDP volatility indicates the power of oil price shock to generate cycles. In addition, the results of the traditional Granger causality test confirm the Markov-Switching Granger Causality (MS-GC) test in all countries except export from the UK.

Implication — Identification the main driver of business cycles is very significant to formulate the steady growth path so that the government able to select the most adequate economic policy.

Originality — The novelty of this study is the adoption of a new approach by combining stylized facts and MS-VAR and MS-Granger causality to analyze the business cycles in different regime.

Keywords — Business cycles, causal variables, MSVAR, MS-Granger Causality.

Introduction

Business cycles are defined as frequent and broad-based movements in an aggregate economic activity where expansionary periods are pursued by contraction (Burns & Mitchell, 1946). The empirical relationships of business cycles between output and other economic variables are often referred to as "stylized facts" (Kydland & Prescott, 1990). As mentioned by Alp and Kilinç (2014), it is necessary for policymakers to understand the sources and properties of business cycles and to

P ISSN 2086-3128 | E ISSN 2502-180X

develop more structural models. For example, documentation of the stylized facts of business cycles is an important tool for constructing theoretical models as statistical benchmarks and for evaluating the validity of the different theoretical models.

According to Diebold and Rudebusch (1996) the Burns and Mitchell's definition of business cycles has two key features. The co-movement between individual economic variables is the first feature. Indeed, the co-movement among series was the centerpiece of Burns and Mitchell's methodology, considering possible leads and lags in timing. Burns and Mitchell's second significant factor in defining business cycles is their division of business cycles into separate phases or regimes. Many of existing studies have witnessed a synthesis of co-movement and nonlinearity features of cycles, such as Diebold and Rudebusch (1996), Chauvet (1998), Carriero and Marcellino (2007), and Buss (2010). There is room for analysis by incorporating both factor structure and regime-switching. In fact, these studies indicated that it could be useful in evaluating the turning points in business cycles if the leading indicators were to be applied to Markov-switching models (MS).

In the same context, Moradi (2016) argues that the formation of dynamic factor models and the composition of indices resulted in the first feature and the second one inspired the use of nonlinear regime-switching models with the seminal work of Hamilton (1989). Since Hamilton's model of the US business cycle until recent years, the Markov-switching autoregressive model has become increasingly popular for the empirical characterization of macroeconomic fluctuations. Various studies examining the business cycle dynamics of economic growth to date have estimated the regime-switching models for example Medhioub and Eleuch (2013), Burzala (2012) and Billio, Ferrara, Guégan, and Mazzi (2013) for the surveys on the regime-switching models. These studies are based on the movement of single series such as Real Gross Domestic Product (GDP) or Industrial Production Index (IPI).

For considering co-movement and estimating a common regime probability of a set of variables, Krolzig (1997) proposes a multivariate extension of this model by developing an MS-VAR process. Clements and Krolzig (2003) addressed the characterization and testing of business cycle asymmetries based on models of MS-VAR in later studies. By using a multi-move Gibbs sampler, (Pelagatti, 2011) estimated a duration-dependent MS-VAR model because the computational burden of using the MLE approach for such models is high.

Lee, Liang, and Chou (2013) argue that the MS-VAR model carries the characteristics of the univariate MS model with its capabilities to differentiate cycle states and capture the sustainability of states. It also reflects the co-movement between the time series and economy series in which prior univariate MS models failed to address. However, since the direction of causality between the variables is not clear, co-movements may only serve as a starting point for further studies purposing to acknowledge the causal relationships. The MS-VAR model is very useful to spot the causal relationships and treat the changes in causality as random events governed by the Markov process such that it could capture the instability of Granger causality between variables. It is a kind of VAR model where the intercept, parameter coefficients, and error term are all subject to Markov-switching.

Understanding the causes of the cyclical fluctuations is very significant, since better economic planning subjects to recognition of the causes of this fluctuation. On the other hand, understanding the causes of the cyclical fluctuations helps to find a steady growth path. Therefore it is important to analyze the causes or driving forces behind the economic fluctuations to select the most adequate government policy.

According to the empirical study by Camacho and Perez-Quiros (2002), the combination of MS models and non-parametric models derived the best out-of-sample forecasting performance. The objective of this paper is to determine the stylized facts of business cycles of countries namely Iran, the US, the UK, and Canada, within the period 1970:Q1-2015:Q4. The paper also determines the foremost cyclical characteristics like volatility and co-movement to identify the predominant drivers of business cycles using the most important leading indicator series. Furthermore the paper identifies the causal relationship between the variables using the MS-VAR method to enhance the understanding of the business cycle.

Methods

The quarterly data sources from the websites of the Federal Reserve Bank of St. Louis, World Bank Open Data, the Main Economic Indicators published by the OECD, and the Central Bank of Iran. The central bank of Iran have elaborated quarterly series of the component of aggregate demand and supply since 1988. Quarterly data between 1970 and 1988 was obtained through the method of a related series of Chow and Lin (1971). The data are adjusted seasonally since we are interested in the percentage (rather than absolute) deviations from trend. All data are expressed in logarithms and a cyclical component of variance is obtained through the double Hodrick and Prescott (1997) filter.

In this paper, we are going to use the double-HP approach suggested by the OECD system of leading indicators. Following the framework described in Arby (2001), Arby (2001), the HP filter is employed in two steps to separate these components. Firstly, the time series is decomposed and long-run trend (T_t) is eliminated by subtracting the trend from the original series (y_t). We get a new series (Z_t) that contains the cyclical and irregular component:

$$Z_t = y_t - T_t = C_t + I_t \tag{1}$$

In the second step, with using again the HP filter on $(\mathrm{Z_t})$, we will obtain the smooth component which is a cycle (C_t). The difference between $(\mathrm{Z_t})$ and (C_t) demonstrates shocks or irregular component $(\mathrm{I_t})$ calculated conforming to the following equation:

$$Min\,\{\textstyle\sum_{t=1}^{T}(Z_t - C_t)^2 + \lambda \sum_{t=2}^{T-1}[(C_{t+1} - C_t) - (C_t - C_{t-1})]^2\} \tag{2}$$

$$I_t = Z_t - C_t \tag{3}$$

Selection of Leading Variables

In this section, we move on to derive the leading variables among 15 macroeconomic variables for each country. In particular, the focus is on two main statistics considered in the literature as standard statistics to elucidate business cycle attributes of the related times series: (1) Relative volatility, defined as the standard deviation of each variable relative to the standard deviation cyclical component of GDPs (δ_x/δ_y). The relative volatility coefficient measures how unstable is variable x with respect to GDP. It corresponds to the ratio between the standard deviation of the x cycle and the standard deviation of the GDP cycle. As stated by Kamil and Lorenzo (2005) levels of cyclical volatility are classified according to the following convention: high (relative volatility greater than 2), medium (relative volatility greater between 1 and 2), and low (relative volatility smaller than 1). A highly volatile variable cannot be associated immediately with causality unless it also presents a cyclical pattern. (2) Co-movement, defined as the degree of contemporaneous co-movement of the variable relative to GDP. Co-movement analysis is typically made up of two aspects: time and direction. In terms of time, phase change of the variable with respect to the reference cycle series could also be leading, coinciding or lagging series. Referring to direction, they will be procyclical, countercyclical or a-cyclical. Following Agénor, McDermott, & Prasad (2000), the degree of co-movement of a series x_t with GDP (y_t) is by the magnitude of the coefficient of correlation $\rho(j)$, j∈{0,±1,±2...}. It is derived from our series using the same filter HP. The series x_t considered to be procyclic, acyclic or countercyclical if the contemporaneous correlation $\rho(0)$ is positive, zero or negative, respectively. If some of the significant cross-correlation coefficients are negative and some are positive and the largest of these are close to each other, then the cyclical properties of this variable are not clear. Furthermore, if $|\rho(j)|$ is a maximum for a positive "*j*" we say that x_t leads the cycle by "*j*" periods, is coincident if $|\rho(j)|$ is a maximum for j=0, and lags the cycle if $|\rho(j)|$ is a maximum for a negative "*j*". If the co-movement pattern of the variables is not clear then the phase shift will be also not clear. Furthermore, if the counter cyclicality or procyclicality is observed both at positive and negative periods at similar levels, then the phase shift is going to be again not clear.

Markov-Switching Vector Auto Regression (MS-VAR)

In the Markov-Switching Vector Autoregressive Model (MS-VAR), the variables under examination change their behaviors during the time, i.e. switches between regimes. The basic idea behind this class of regime-switching models is that the parameters of the VAR process will be regime dependent or depend on the state (regime) variable (s_t) which is an unobservable variable. In other words, the parameters of a K-dimensional vector time series process $\{y_t\}$ depend on an unobservable regime variable $s_t \in \{1,\ldots,M\}$, which represents the probability of being in a particular state of the world.

$$p(y_t|Y_{t-1},s_t) = \begin{cases} f(y_t|Y_{t-1},\theta_1) & if\ s_1 = 1 \\ \vdots & \vdots \\ f(y_t|Y_{t-1},\theta_M) & if\ s_t = M \end{cases} \tag{4}$$

Where Y_{t-1} denotes all the observations of $\left[\,y_{t-j}\right]_{j=1}^{\infty}$ $and\ \theta$ show the parameters of the VAR model. In every regime y_t is generated by a VAR process of order q as follows:

$$y_t = \mu(s_t) + \sum_{i=0}^{q} A_i(s_t)y_{t-i} + u_t \tag{5}$$

$$u_t \sim NID(0,\sum(s_t))$$

Where $\mu(.)$ shows the intercepts or mean in each regime, $A_i(.)$ is a matrix and shows the coefficients of the lagged values of the variable in different regimes, and $\sum$ shows the variance of the residuals in each regime. To complete the data generating process assumptions about the regime generating process (s_t) are needed.

In MS-VAR models the regime-generating process (s_t) is produced by a Markov chain:

$$Pr[s_t|\{s_{t-1}\}_{i=1}^{\infty},\{y_{t-1}\}_{i=1}^{\infty}] = Pr\{s_t|s_{t-1};\rho\} \tag{6}$$

Where ρ includes the probability parameters. The result is that the current regime (s_t) depends only on the regime one period ago (s_{t-1}). Thus the transition probabilities could be shown as:

$$P_{ij} = P\left\{s_{t=j}\middle|s_{t-1} = i, s_{t-2} = k, \ldots\right\} = \Pr\left\{s_{t=j}\middle|s_{t-1} = i\right\} \tag{7}$$

$$,\sum_{j=1}^{M} P_{ij} = 1\ \forall i,j \in \{1,\ldots,M\}$$

Where (P_{ij}) gives the probability that state (*i*) will be followed by state (*j*) and $0 \leq P_{ij} \leq 1$. These transition probabilities can be indicated in an $(M \times M)$ transition matrix:

$$p = \begin{bmatrix} p11 & p12 & \cdots & p1M \\ p21 & p22 & \cdots & p2M \\ \vdots & \vdots & \vdots & \vdots \\ pM1 & pM2 & \ldots & pMM \end{bmatrix} \tag{8}$$

According to Krolzig (1997), in the general specification of MS-VAR model, all autoregression parameters are conditioned on the state (s_t) of the Markov chain. So, equation (9) can be written as:

$$y_t = v(\varepsilon_t) + A_1(\varepsilon_t)y_{t-1} + \cdots + A_p(s_t)y_{t-p} + u_t \tag{9}$$

Pursuant to Krolzig (1997) in the most general specification of an MS-VAR model, all parameters of the auto regression are conditioned on the state (s_t) of the Markov chain such that each regime $m\ VAR(p)$ parameterization $v(m)$ (orμ_m), $\Sigma_m, A_{1m}, \ldots, A_{jm}, m = 1, \ldots, M$ such that:

$$y_t = \begin{cases} v_1 + A_{11}y_{t-1} + \cdots + A_{p1}y_{t-p} + \sum_1^{1/2} u_t\ if\ s_1 = 1 \\ \vdots \\ v_M + A_{1M}y_{t-1} + \cdots + A_{pM}y_{t-p} + \sum_M^{1/2} u_t\ if\ s_1 = M \end{cases} \tag{10}$$

Where $u_t \sim NID(0, I_k)$.

Estimation of MS-VAR models are in many empirical analyses based on the EM algorithm suggested by Hamilton (1989). The EM algorithm has been designed to estimate the parameters of a model where the observed time series depends on an unobserved or a hidden stochastic variable. The iterative estimation technique can be used to make inference for $t = 1,2,\dots,T$, while taking the previous value of this probability $\xi_{it-1} = P_r\{s_{t-1} = i|\Omega_{t-1};\theta\}$ as an input. The conditional log-likelihood can be given by:

$$logf(y_1, y_2, \dots, y_T|y_0;\theta) = \sum_{t=1}^{T} logf(y_t|\Omega_{t-1};\theta) \quad (11)$$

Markov Switching Granger causality (MS- GC)

The methodology requires the estimation of either an MSIA(.)-VAR (.) or an MSIAH (*p*)-VAR (*q*) model. Based on the coefficients of the lagged values we can determine the direction of the Granger causality in the equation for each variable. For example, in countries with three variables the model is given as:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \mu_{1,s_t} \\ \mu_{2,s_t} \\ \mu_{3,s_t} \end{bmatrix} + \sum_{k=1}^{p} \begin{bmatrix} A_{11,s_t}^{(k)} & A_{12,s_t}^{(k)} & A_{13,s_t}^{(k)} \\ A_{21,s_t}^{(k)} & A_{22,s_t}^{(k)} & A_{23,s_t}^{(k)} \\ A_{31,s_t}^{(k)} & A_{32,s_t}^{(k)} & A_{33,s_t}^{(k)} \end{bmatrix} \begin{bmatrix} y_{1,t-k} \\ y_{2,t-k} \\ y_{3,t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,s_t} \\ \epsilon_{2,s_t} \\ \epsilon_{3,s_t} \end{bmatrix} \quad (12)$$

In the y_{1t} vector, y_{2t} and/or y_{3t} is/are Granger cause of y_{1t} in each k^{th} regime if the parameter set or sets of $A_{12}^{(k)}$ and $A_{21}^{(k)}$, and/or $A_{13}^{(k)}$ and $A_{31}^{(k)}$ are statistically different from zero. In general, Granger causalities can be detected by testing $H_0: A_{12}^{(k)} = 0$ and $H_0: A_{21}^{(k)} = 0$, $H_0: A_{23}^{(k)} = 0$ and $H_0: A_{32}^{(k)} = 0$, and $H_0: A_{13}^{(k)} = 0$ and $H_0: A_{31}^{(k)} = 0$.

Results and Discussion

Selection of Causal Variables

As mentioned by Pacheco Jiménez (2001) the stylized facts is very beneficial to evaluate causal relationships because a typical "causal" variable shows a leading, procyclical, and highly volatile behavior. This suggests, but not confirms, causality respect to GDP. Table 1 provides the statistical relationships between real GDP and 15 other variables. The variables are seasonally adjusted and taken logarithms before calculating the volatility and correlation.

The results indicate that the volatility of GDP in Iran is much higher than other industrialized countries studied in the study. Based on Male (2011), higher output volatility reflects, the vulnerability of Iran's developing economy and its inability to diversify risks or perform stabilizing macroeconomic. Moreover, consumption, investment, exports and imports in all countries are found to be often procyclical. On the other hand, the consumption of durable goods and machinery investment has a high relative volatility. Government final consumption in Iran, unlike other countries, has a positive contemporaneous correlation and also procyclical.

The relative volatility in the unemployment rate is high in all countries, but its contemporaneous correlation is negative and it does not show a clear pattern. Regarding monetary variables, it can be mentioned that narrow money in the UK and Canada are recognized as the main driver of the business cycle. The consumer price index (CPI) has low relative volatility, negative contemporaneous correlation, and countercyclical behavior in all countries. The high level of oil price volatility relative to the GDP volatility in all countries, except for Iran, implies the ability of oil price shock to generate cycles. Meanwhile the lower level in Iran, perhaps can be explained simply by the extremely high output volatility experienced in Iran. On the other hand, the phase shifts in all countries are coincident or not clear.

In the next step, the integration order of the variables were determined using the point optimal test of Hylleberg, Engle, Granger, and Yoo(1990)–HEGY test and Ng and Perron (2001)–NGP test were determined before testing causality. In the second step, the maximum likelihood procedure of Johansen is utilized for the determination of the possible existence of cointegration between variables.

Table 1. Statistical relationships between real GDP and other variables

	US	Canada	UK	Iran
Real GDP				
Volatility	1.428	1.332	1.505	7.289
Autocorrelation (t, t-1)	0.942	0.928	0.939	0.954
Private consumption expenditure				
Relative Volatility	0.836	0.522	0.952	0.680
Contemporaneous Correlation	0.904	0.761	0.032	0.562
Cyclicality	Procyclical	Procyclical	countercyclical	Procyclical
Phase Shift	Lead (.921)	Coincidental	lag(-0.241)	lag(-0.577)
Durable goods				
Relative Volatility	2.402	2.368	2.634	2.957
Contemporaneous Correlation	0.814	0.740	0.672	0.108
Cyclicality	Procyclical	Procyclical	Procyclical	countercyclical
Phase Shift	Lead (0.876)	Lead (0.748)	Coincidental	Lag (0.259)
Non-durable goods				
Relative Volatility	1.255	0.501	1.235	0.660
Contemporaneous Correlation	0.270	0.698	0.464	0.469
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	lag(.445)	Lag (0.733)	Lag (0.481)	Lag (0.530)
Services				
Relative Volatility	0.503	0.690	0.820	0.945
Contemporaneous Correlation	0.335	0.786	0.888	0.442
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Coincidental	Coincidental	Coincidental	Coincidental
Fixed Investment				
Relative Volatility	2.972	2.642	2.759	1.547
Contemporaneous Correlation	0.962	0.732	0.873	0.436
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Coincidental	Coincidental	Coincidental	Lead (0.442)
Construction Investment				
Relative Volatility	6.770	2.329	3.614	1.362
Contemporaneous Correlation	0.725	0.652	0.633	0.232
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Lead (.852)	Coincidental	Coincidental	Lead(0.493)
Machinery investment				
Relative Volatility	3.669	4.427	3.635	2.996
Contemporaneous Correlation	0.841	0.706	0.637	0.232
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Lead (.866)	Coincidental	Lag (.654)	Lead (.310)
Government final consumption				
Relative Volatility	0.685	0.656	0.500	0.724
Contemporaneous Correlation	-0.366	-0.222	-0.289	0.531
Cyclicality	countercyclical	countercyclical	countercyclical	Procyclical
Phase Shift	Coincidental	Lag (-0.363)	Lag (-0.312)	Lag (.546)
Exports				
Relative Volatility	2.731	2.741	2.050	2.336
Contemporaneous Correlation	0.498	0.767	0.543	0.566
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Lag (-0.634)	Lag (.768)	Lead (.558)	Lead (.611)
Imports				
Relative Volatility	3.284	3.184	2.188	1.893
Contemporaneous Correlation	0.878	0.813	0.800	0.417
Cyclicality	Procyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Coincidental	Coincidental	Coincidental	Coincidental
Narrow Money (M1)				
Relative Volatility	6.488	2.133	2.018	0.893
Contemporaneous Correlation	0.009	0.249	0.598	0.207
Cyclicality	Acyclical	Procyclical	Procyclical	Procyclical
Phase Shift	Not Clear	Lead (0.343)	Lead (0.679)	Coincidental
Broad Money (M3)				
Relative Volatility	0.854	1.545	2.036	0.800
Contemporaneous Correlation	0.101	0.147	-0.118	0.208
Cyclicality	Procyclical	Not Clear	countercyclical	Procyclical
Phase Shift	Lead (0.347)	Not Clear	Lead (-0.476)	Lead(0.213)
CPI				
Relative Volatility	0.908	0.977	1.144	1.369
Contemporaneous Correlation	-0.458	-0.513	-0.709	-0.210
Cyclicality	countercyclical	countercyclical	countercyclical	countercyclical
Phase Shift	Lead (-0.689)	Lag (-0.638)	Coincidental	Lead (-0.328)
Oil Price				
Relative Volatility	11.236	12.396	10.898	3.099
Contemporaneous Correlation	0.116	0.322	0.107	0.338
Cyclicality	Not Clear	Procyclical	Not Clear	Procyclical
Phase Shift	Not Clear	Coincidental	Not Clear	Coincidental
Unemployment				
Relative Volatility	8.077	6.254	5.391	9.569
Contemporaneous Correlation	-0.894	-0.851	-0.722	-0.060
Cyclicality	countercyclical	countercyclical	countercyclical	Acyclical
Phase Shift	Lead (-0.918)	Lag (-0.865)	Lag (-0.823)	Not Clear

The results indicate that the null hypothesis of a unit root cannot be rejected at the 5 % level of significance. On the other hand, the first differences of variables appear to be stationary. As a result, we can say that the variables are integrated of order one, I(1). Since the variables are integrated of the same order, the maximum likelihood procedure of Johansen can be used to examine the possible existence of cointegration between the variables. According to the results, the null hypothesis of no cointegration could not be rejected. Because they are not cointegrated, the first difference or innovations of the variables can be used to test for MS- Granger.

MS-VAR and MS-Granger Causality Test Results

The first difference or innovations of the variables is used to Markov Switching- Granger causality analysis. Before estimating the MS models, a linear VAR model is specified. The lag length is determined by using information criteria such as AIC and SIC. Next, the MSIA and MSIAH models are estimated for each country using the selected optimal lags assuming two and three regimes. In these models, for determining the number of regimes, we firstly tested linear VAR model against an MS-VAR model with two regimes. The H_0 hypothesis will reject linear hypothesis by using LR test statistics for all countries.

Next, MS-VAR model with two regimes are tested against its alternative with three regimes. The null hypothesis, which indicates superiority of model with two regimes, was rejected based on calculated LR statistic.

Iran

The MSIA(2)-VAR(4) model, which is the first model to be analyzed, is estimated for the IRAN and the results are given in Table 2. Based on the transition probabilities, the most persistent regime is regime number 2 and the probability of staying in this regime is 67%. On the other hand, the tendency to remain in regime 1 is extremely low (14%). The business cycle phases with the majority of observations (129 quarters) exist in regime 2.

Table 2. Regime properties of the MSIA (2)-VAR (4) model for IRAN

	Number of Observations	Probability	Average Duration	Transition probability		
Regime 1	43	25.00	1.13	Regime 1:	0.14	0.86
Regime 2	129	75.00	3.31	Regime 2:	0.33	0.67

To find the potential similarities and differences of causality, these results are compared with traditional causality tests in Table 3.

Table 3. MS-Granger and Linear Granger causality results for IRAN

Regime 1			Regime 2		
Exp	↔	gdp	Exp	←	gdp
Mach	↔	gdp	Mach	none	gdp

Causality Direction	χ^2	Prob.	Causality Decision
Δgdp → Δexp	3.70	0.44	No
Δgdp → $\Delta mach$	5.69	0.22	No
Δexp → Δgdp	71.39	0.00	Yes
$\Delta mach$ → Δgdp	8.43	0.07	Yes

The results indicate that there is unidirectional traditional Granger causality from export to GDP, while there is bidirectional MS-Granger causality between exports to GDP in regime 1 and unidirectional from GDP to exports in regime 2. Furthermore, there is evidence to support unidirectional traditional Granger causality from machinery investment to GDP, while there is bidirectional MS-Granger causality between machinery investment and GDP in regime 1.

United States

The estimation results of MSIAH(2) -VAR(3) model for the US are given in Table 4. As it's clear, probability of remaining in regime 1 is calculated at 66 % while the probability of shifting to regime 2 is 34%. The possibility of proceeding to the first regime from the second regime is very high (76%), whereas the possibility of staying in the second regime is 24%.

For comparative purposes, the traditional linear Granger causality test results and summary of the MS-Granger causality test results are exhibited in Table 5.

Table 4. Regime properties of the MSIAH (2)-VAR (3) model for the US

	Number of observation	Probability	Average Duration	Transition probability
Regime 1	120	69.77	3.00	Regime1: 0.66 0.34
Regime 2	52	30.23	1.30	Regime2: 0.76 0.24

Table 5. MS-Granger and Linear Granger causality results for the US

Regime 1		Regime 2	
dur ↔ gdp		dur ↔ gdp	
con → gdp		con ← gdp	
mach → gdp		mach ← gdp	
Causality Direction	χ^2	Prob.	Causality Decision
Δgdp → Δdur	3.99	0.26	No
Δgdp → Δcon	3.32	0.34	No
Δgdp → Δmach	7.00	0.07	Yes
Δdur → Δgdp	10.93	0.01	Yes
Δcon → Δgdp	27.09	0.00	Yes
Δmach → Δgdp	20.68	0.00	Yes

Based on the traditional Granger causality test, there is a unidirectional relationship running from durable consumption to GDP, but the bidirectional relationship is accepted in all regimes. Whereas for the causal relationship between GDP and construction investment, we found traditional Granger causality running from construction investment to GDP. On the contrary unidirectional relationship from GDP to construction investment is only found in regime 2. Moreover, there is a bidirectional traditional Granger causality between GDP and machinery investment. However the results of MS-Granger causality tests show that there is a unidirectional relationship running from machinery investment to GDP in regime 1 and from GDP to machinery investment in regime 2.

Canada

Table 6 portrays the MSIAH(3)-VAR(2) model as the best fit to Canadian data. In this country, the business cycle phase with the most duration is the first phase (19 quarters on average). The transition probabilities suggest the persistence of regime (1) is higher than other ones (0.85).

Table 6. Regime properties of the MSIAH (3)-VAR (2) model for CANADA

	Number of Observations	Probability	Average Duration	Transition Probability
Regime 1	95	69.34	19.00	Regime1: 0.95 0.04 0.01
Regime 2	21	15.33	3.00	Regime2: 0.24 0.68 0.08
Regime 3	21	15.33	7.00	Regime3: 0.00 0.15 0.85

In order to find the potential similarities and differences of causality, these results are compared with traditional causality tests in Table 7. The results indicate that there is a bidirectional traditional Granger causality between GDP and durable consumption, which corresponds with the results of MS-Granger causality tests in regime 1. Moreover, there is unidirectional traditional

Granger causality from narrow money to GDP which is consistent with results obtained for regimes 1 and 3.

Table 7. MS-Granger and Linear Granger causality results for the CANADA

regime 1	regime 2	regime 3	
dur ↔ gdp	dur None gdp	dur None gdp	
m_1 → gdp	m_1 ← gdp	m_1 → gdp	
Causality Direction	χ^2	Prob.	Causality Decision
Δgdp → Δdur	6.64	0.03	Yes
Δgdp → Δm_1	2.98	0.22	No
Δdur → Δgdp	12.52	0.00	Yes
Δdur → Δm_1	2.76	0.25	No
Δm_1 → Δgdp	5.89	0.05	Yes
Δm_1 → Δdur	17.08	0.00	Yes

United Kingdom

Table 8 represents the results of estimated MSIAH(3)-VAR(3) model for UK. The transition probability matrix shows that the first two regimes are more persistent than regime 3. Furthermore, regimes 1 and 2 include 89 and 75 quarters, respectively.

Table 8. Regime properties of the MSIAH (3)-VAR (3) model for the UK

	Numberof observation	Probability	Average Duration	Transition probability
Regime 1	89	49.44	4.24	Regime1: 0.75 0.18 0.07
Regime 2	75	41.67	3.95	Regime2: 0.24 0.75 0.01
Regime 3	16	8.89	2.67	Regime3: 0.12 0.26 0.62

The comparison between traditional linear Granger causality test and the MS-Granger causality test are exhibited in Table 9.

Table 9. MS-Granger and Linear Granger causality results for the UK

regime 1	regime 2	regime 3	
exp None gdp	exp ↔ gdp	exp ↔ gdp	
m_1 ↔ gdp	m_1 ↔ gdp	m_1 → gdp	
Causality Direction	χ^2	Prob.	Causality Decision
Δgdp → Δexp	**12.25**	**0.00**	**Yes**
Δgdp → Δm_1	**14.09**	**0.00**	**Yes**
Δexp → Δgdp	0.37	0.94	No
Δm_1 → Δgdp	**22.09**	**0.00**	**Yes**

In line with the traditional Granger causality test, there is a unidirectional relationship running from GDP to export. The bidirectional relationship in the MS-Granger causality test exhibit in regime 2 and regime 3. Moreover, bidirectional traditional Granger causality between GDP and narrow money is found for regimes 1 and 2 while, our findings confirmed existence of unidirectional causality from narrow money to GDP in regime 3.

Key Findings of Estimated MS Models

The probability of the business cycle remaining in regime 1 was longer than other regimes. The business cycle phases with the number of observations of each regime's existence in regime 1 suggest the persistence of this regime in the US, Canada, and the UK. The average duration shows a similar pattern in the business cycle in all countries except Iran. The longest average duration with 19 quarters is registered in the first regime of Canada and the highest number of observation with 129 quarters in regime 2 is recorded in Iran. The transition probability matrix shows that all the regimes are persistent in all countries except the probability of remaining in the second regime in the US and the possibility of staying in the first regime of Iran.

In general business cycle in Iran is relatively different to the other OECD countries. The factors underlying this difference are an Iran's single-product (oil) economy, different degrees of development and the lack of a strong business relationship with foreign countries, especially after the revolution in Iran. As a result, these factors lead to restrain in the exports of oil, imports of investment in intermediate goods, extra financial costs, and severe fluctuations in Iran's GDP.

According to the results obtained by the MS-VAR and MS-Granger causality approach, all studied variables are recognized as the main driver of business cycle at least in one regime. Nevertheless, the results of the traditional Granger causality test confirm the MS-Granger causality test results in all countries except export from the UK.

The result of the first step in trying to identify the main driver of the business cycle using some selected macroeconomic time series is similar to some previous works including De Medeiros and Sobral (2011), Camacho and Perez-Quiros (2002), and Misas and Ramírez (2007). Findings of the second step of recognizing the direction of causality are in lin e to those studies based on MS-VAR and MS-Granger causality test like Bildirici (2013), Hyera and Mutasa (2016), Claessens, Kose, & Terrones (2012) and Billio, Anas, Ferrara, & Duca (2007). No prior studies, however, have highlighted both steps and the novelty of this paper lies in the combination of both steps.

Conclusion

This study attempted at uncovering drivers of business cycles by presenting evidence from Iran, the US, the UK, and Canada for the 1970:Q1-2015:Q4 period. The first objective is to find the main driver causing the business cycle by using the stylized facts of business cycles of countries surveyed. The second goal of the study is to recognize the direction of causality, based on MS-VAR and MS-Granger causality approach to evaluate causality in different regimes of the business cycle and compares the result with the traditional Granger causality test.

The results revealed higher volatility of GDP in Iran compared to three developed countries. However, we find some similarities within the US, the UK, and Canada regarding the probability of a business cycle, number of observations, and the average duration, especially in the first regime of MS-VAR models. Export and machinery investment in Iran are Granger causes of GDP in the only regime 1. The causal variable in the US could be durable consumption, construction investment, and machinery investment. MS-Granger analysis results show that durable consumption is the Granger cause of GDP in all regimes, but machinery investment and construction investment are Granger causes of GDP in the only regime 1. According to the results obtained for Canada, durable consumption and narrow money can be considered as Granger causes of GDP in regime 1. Meanwhile, export and narrow money play the same role in the UK. Furthermore, export in regime 2 and regime 3 and narrow money in all regimes are the Granger causes of GDP based on the MS-Granger causality method. In addition the results of the traditional Granger causality test confirm the MS-Granger causality test results in all countries except from the UK's export.

Due to limited access to data for countries that may affect oil prices and the lack of seasonal variables in Iran, this paper focuses only on four countries. This may limit generalizability of the results. Accordingly, performing more research at the regional and international levels with a larger number of countries are recommended.

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