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Herd Behavior Demand and Supply Shocks on Business Cycle: An Empirical Analysis in Iran

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Abstract: The central objective of our paper is to empirically investigate the effect of demand and supply shocks as sources of Business cycle in the Iranian economy. In particular, this study examines the existence of herd behavior among shocks as well as fiscal, monetary, financial, technology and oil shocks in the Business cycle in Iran. In methodology, the study analyzes the herd behavior by estimating vector error correction (VECM) model using annual data covering the period of 1974 to 2008. Also, we adopt an innovation accounting by simulating variance decompositions (VDC) and impulse response functions (IRF) for further inferences. The findings support the idea that there is a strong herd behavior among shocks on business cycle in Iran.

Key words: *shocks, herd behavior, VECM, Var, Impulse Response, Variance decomposition*

INTRODUCTION

Traditional Keynesian theory emphasizes the central role of demand-side factors such as fiscal and monetary shocks in macroeconomic fluctuations .For example in late 1970s, the leading economists of major schools of thought such as Tobin, Friedman and Lucas all agreed that the rate of growth of the money supply has a real effect on the economy and plays an important role in explanation of the output fluctuation. New-Keynesian theorists focus on the relevance of nominal shocks .In contrast, real business cycle (RBC) models predict that technological shocks generate most of business cycles(see,eg.,kydland and Prescott ,1982).The Nelson and Plosser (1982) argument is that most of the fluctuations in these variables should be attributed to the trend component, in trend versus cyclical decomposition, which would presumably be unaffected by monetary shocks. The above studies along with supply shocks associated with the two oil price increases of the 1970s and failure of the demand oriented Keynesian models to account adequately for rising unemployment accompanied by accelerating inflation stimulated the transition from monetary to real theories of business cycles.

The business cycles in the economy of Iran have been studied within the individual shocks. An area of novelty of this study is that it analyzes Herd behavior shocks rather than individual shock as sources of Business cycle in economy of Iran. Another contribution of this paper is to use ICT shocks as a technology shocks, because the diffusion of ICTs increase output growth in the medium to long term via capital deepening effects and total factor productivity gains and in the short term via lagged adjustment of wages to productivity gains. The rest of the paper is organized as follows: the next section provides some background empirical information on effect shocks in the business cycles. In particular, this section highlights shocks behavior of the top five major shocks in the business cycles. Section 3 presents the *Model, Data, and estimation Methodology*. Section 4 highlights the empirical findings including the data preliminaries and the results based on the unrestricted VAR and VECM tests. Further inferences are then made based on the VDC and IRF analysis. Finally, section 5 concludes and draws several policy recommendations from the major findings of the paper.

2. Relevance Empirical Literatures:

Many studies have empirically examined the roles of technology shocks in the business cycles in order to evaluate the plausibility of the technology-driven real business cycle hypothesis. A seminal work is by Gal's

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(1999), who proposes identifying technology shocks by a bivariate structural vector auto regression (SVAR) model consisting of labor productivity growth and hours worked. He develops the long-run restriction that only technology shocks permanently affect the level of labor productivity. This idea is very attractive in that the restriction seems theoretically robust and the method doesn't use Solow residuals, which may be affected by non-technological factors such as unobservable factor utilization variations. By applying the SVAR to U.S. data, he shows that identified technology shocks dampen hours worked. This result has attracted much attention, since it is opposite to the prediction of the standard real business cycle model. In the subsequent work, Gal´ı (2005) shows that the result is basically common across the G-7 countries except for Japan. Many researchers have investigated potential flaws in his method. Broadly speaking, those are categorized into three classes. The first is a bias due to reducing the underlying economy to a finite ordered VAR model. This is emphasized by Chari, Kehoe, and McGrattan (2004), although Erceg, Guerrieri, and Gust (2005) and Christiano, Eichenbaum, and Vigfusson (2006) show that the bias appears to be not so problematic or be methodologically reduced. The second is that results derived from the long-run restriction are extraordinarily affected by the low frequency correlation between variables in the system, even if the correlation is not causal. This is examined by Fernald (2007) and Francis and Ramey (2008). The third is the possible misidentification of non-technology shocks as technology shocks. Such misidentification can happen since certain types of non-technology shocks permanently affect labor productivity via the level of capital-labor ratio. The shock examined often in the literature is a capital tax shock. This paper calls such shocks as the *non-technology permanent shocks* and develops a method to identify those. The method is applied to the G-7 countries' data.

Charles Nolan & Christoph Thoenissen (2009) show that financial shocks are very tightly linked with the onset of recessions, more so than TFP or monetary shocks. The financial shock invariably remains contractionary after recessions have ended. The financial accelerator shock accounts for a large part of the variance of GDP is generally much more important than money shocks and is strongly negatively correlated with the external finance premium.

Since the 1970s, and at least until recently, macroeconomists have viewed changes in the price of oil as an important source of economic fluctuations, as well as a paradigm of a global shock, likely to affect many economies simultaneously. Such a perception is largely due to the two episodes of low growth, high unemployment, and high inflation that characterized most industrialized economies in the mid and late 1970s. Conventional accounts of those episodes of stagflation blame them on the large increases in the price of oil triggered by the Yom Kippur war in 1973, and the Iranian revolution of 1979, respectively.

The approach in this paper is to concentrate on five key drivers of the business cycle :monetary and fiscal shocks, Domestic credit to private sector (% of GDP) as financial shocks, ICT shocks as a technology shocks, and oil shocks.. By focusing on a limited number of familiar shocks, our aim is to understand the incremental contribution of ICT shocks.

3. *Model, Data, and Estimation Methodology:*

3-1.Data and Variables:

The annual data for all variables except ICT the period 1974-2008 obtained from central Bank of Iran. Total annual investment in telecom of Iran (ICT data) obtained from The World Telecommunication/ICT Indicators Database(2009). The variable of GDP in 1997 prices used as the criterion of output and the variables of the government expenditures including the current and development expenditures in 1997 prices (G), have used as the variables related to the fiscal shocks and currency (M2) have been used as monetary measures. Domestic credit to private sector (% of GDP) as financial shocks (privy), ICT shocks as a technology shocks, and oil shock (oilrev). All variables are expressed in their logarithmic transformation, Δ denotes the first difference operator.

To evaluate the integration properties of the variables, we employ standard augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (Dickey and Fuller, 1981; Phillips and Perron, 1988). A variable is said to be integrated of order d, written $I(d)$ if it requires differencing d times to achieve stationarity. For cointegration, we employ the VAR based tests of Johansen (1988) and Johansen and Juselius (1990).

3-2.The Model:

Beginning in the early 1980s vector auto regressions (VAR) emerged as an important vehicle for the empirical analysis of macroeconomic times series. VARs have been attractive research tools for at least three reasons. First, they offer a convenient way to characterize data without having to invoke economic theory to restrict the dynamic relations among variables. Second, many completely specified economic models give rise

to VAR representations of the variables in the model. As a result VARs have been widely exploited for both data description and model characterization. Third, VARs can be readily transformed to interpret the evolution of the system's variables as a function of orthogonalized 'innovations' in any of these variables. Cooley and Leroy (1985), among others, describe the relation between identification and notions of causality and exogeneity as they apply to VARs.

To test the herd behavior among shocks, the vector autoregressive (VAR) model is adopted first on all as well as fiscal, monetary, financial, ICT and oil shocks . In this analysis, there is a set of p=6 endogenous variables. Following Johansen(1988,1991) and Johansen and Juselius(1990,1992), we consider a *p*-dimensional vector time series *zt* and model it as an Unrestricted Vector Autoregression (VAR) involving up to *k*-lags of *zt*.

$$z_t = A_1 z_{t-1} + ... + A_k z_{t-k} + \mu + \varepsilon_t, \;\; \varepsilon_t \sim niid(0, \sum) \tag{1}$$

where *zt* is a *(px1)* matrix and each of the *Ai* is a *(pxp)* matrix of parameters. The Johansen approach is used with the consideration that it enables hypotheses tests concerning the matrix and the number of equilibrium relationships to be carried out.

Before test of cointegration could be done, we have to choose the maximum lag length, *k*, in the Unrestricted Vector Autoregression Model (VAR). Choosing the appropriate lag length is important since a *k* too small will invalidate the tests, whereas a *k* too large may result in a loss of power (Kanioura, 2001). The appropriate lag is chosen by checking the residuals of VAR model with one lag after another and the selection of lag is based on the one that has the absence of serial correlation in the residuals.

Being aware of the lag order, then we construct the long-run equations (Unrestricted VAR model) for the series. The analysis is carried out further by doing the Johansen cointegration test with *k-1* lag. The determination of the number of cointegrating vectors is based on the *maximal eigenvalue* and the *trace* tests. The vector error correction model (VECM) restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. In this case, the cointegration terms are the correction terms since a series of partial short-run adjustments correct gradually the deviation from long-run equilibrium. The VECM corresponds to a restricted VAR of order *k-1* for the first differenced series, with the inclusion of error-correction terms for the cointegrating vectors.
We write a *p*-dimensional vector error correction model (VECM) as follows:

$$\Delta y_t = \sum_{i}^{k-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-1} + \mu + \varepsilon_t \;, \; t = 1, \; . \; . \; .T \tag{2}$$

where y_t is the set of $I(1)$ variables discuss above; $\varepsilon_t \sim niid(0,\sum)$; μ is a drift parameter, and Π is a (p x p) matrix of the form $\Pi = \alpha\beta'$ where α and β are both (p x r) matrices of full rank, with β containing the r cointegrating vectors and α carrying the corresponding loadings in each of the r vectors. The adjustment coefficients in matrix α refer to the coefficients of the Error Correction (ECM) terms.

Additionally, we adopt an innovation accounting by simulating variance decompositions (VDC) and impulse response functions (IRF) for further inferences. VDC and IRF serve as tools for evaluating the dynamic interactions and strength of causal relations among variables in the system. The VDC indicate the percentages of a variable's forecast error variance attributable to its own innovations and innovations in other variables. Thus, from the VDC, we can measure the relative business cycles with shocks. Moreover, the IRF trace the directional responses of a variable to a one standard deviation shock of another variable. This means that we can observe the direction, magnitude and persistence of business cycles to variation in Government expenditure, money supply, Domestic credit to private sector (% of GDP) as financial shocks (privy),ICT and oil revenue.

4. Empirical Findings:

As a preliminary step, we first subject each variable to Augmented Dickey Fuller (ADF) unit root tests. The results of the tests are displayed on Table 1. The results generally suggest that most variables are integrated of order one as the null hypothesis that the series are not stationary is accepted at level but rejected at first difference. In other words, the variables are stationary at first difference or I(1).

Table 1: Unit Root Tests

	ADF test statistic (with trend and intercept)		P-P test statistic (with trend and intercept)	
Variable	*Level*	*First Difference*	*Level*	*First Difference*
lnGDP	-2.35	-3.81**	-2.34	-6.48***
lnprrivy	-2.22	-6.55***	-2.25	-6.47***
lnM2	-2.02	-3.61**	-2.25	-3.61**
LnG	-1.56	-5.03***	-3.38*	-6.18***
lnoilrev	-1.63	-6.31***	-1.8	-6.27***
lnICT	.39	-4.05***	.75	-3.39*

4.1 Analysis on Business Cycle in Iran:

The first VAR model developed consists of 6 endogenous variables of shocks: *z = [lnGDP, lnG, lnm2, lnprivy, lnICT, lnoilrev]*. For this model, the maximum lag length, *k*, of 2 is chosen. Based on *Maximum Eigenvalue* and *Trace* tests of cointegration, there are 4 cointegrating vectors existed among the variables. Table 2 provides detail results of these cointegration tests.

Table 2: Johansen Cointegration Tests Results

Null Hypothesis about Rank (r)	*Max-Eigen* Statistic	5% Critical Value	*Trace* Statistic	5% Critical Value
r=0	69.19	40.07	217.13	95.75
r≤1	59.18	33.87	147.94	69.81
r≤2	40.99	27.58	88.75	47.85
r≤3	32.58	21.13	47.76	29.79
r≤4	14.09	14.26	15.17	15.49
r≤5	0.18	3.84	0.18	3.84

Normalising *LNGDP* for cointegrating vector 1, following are the suggested vectors:

CV1 = *LNGDP* - 0.52LNG – 0.21*LNM2* + 0.O2LNPRIVY-0.03LNICT+0.06 LNOILREV-4.63

We then proceed with an estimated error correction model using the 6 variables to illustrate how the cointegration results might be utilised. The vector error correction model (VECM) restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. Table 3 displays 6 short-run equations for Δ LNGDP, Δ LNG, Δ LNM2

Δ LNPRIVY, Δ LNICT, and Δ LNOILREV respectively. All coefficients of short-run equation are coefficients relating to the short run dynamics of the model's convergence to equilibrium and coefficients of lag CV (error correction term) represent the speed of adjustment. From all 6 short-run equations, equation 1 is selected to be used for further inferences as it has at least one lag error correction term ($CV1_{t-1)}$ which is significant with negative sign. The negative sign of the ECM terms or cointegrating vectors is rather better results to be considered since it is the correct sign of the error correction. The significant of an error correction term shows the evidence of causality in at least one direction.

Table 3: The Vector Error Correction Model Dependent variable

variable	Δ(LnGDP) (1)	Δ(LnG) (2)	Δ(Lnm2) (3)	Δ(Lnprivy) (4)	Δ(LinICT) (5)	Δ(Lnoilrev) (6)
constant	0.06	0.03	-0.01	0.02	0.04	.37
?(LnGDP) $_{t-1}$	0.51***	0.05	-0.41*	0.08	0.81*	-1.13
?(LnGDP) $_{t-2}$	0.55***	1.00***	-0.32	0.42*	1.09*	0.21
?(LnG) $_{)\ t-1}$	0.08	-0.39**	0.16	-0.05	0.38	-0.89
?(LnG) $_{)\ t-2}$	0.40***	0.16	0.21**	-0.26**	0.109	0.86
?(Lnm2) $_{t-1}$	-0.06	-0.38**	0.27**	0.29**	0.28	0.06
?(Lnm2) $_{t-2}$	0.25***	0.35**	-0.15	-0.40**	0.16	-0.27
?(Lnprivy) $_{t-1}$	-0.11**	-0.01	0.15**	0.31***	-0.28	-0.40
?(Lnprivy) $_{t-2}$	0.02**	0.14**	0.18	-0.09	-0.06	1.79***
?(LinICT) $_{t-1}$	-0.58***	0.06	0.33**	0.39**	-0.70**	0.38
?(LinICT) $_{t-2}$	-0.33***	-0.54*	-0.07	0.21	-0.79**	2.59**
?(Lnoilrev) $)_{t-1}$	0.03***	0.16***	0.05**	0.04**	-0.04	0.22
?(Lnoilrev) $)_{t-2}$	-0.02*	0.003	0.02	0.01	-0.14**	0.30
R-squared	0.84	0.68	0.59	0.21	0.65	0.36
Adj. R- quared	0.74	0.47	0.32	0.32	0.41	-0.06
Sum sq. esids	0.01	0.05	0.05	0.30	0.07	3.17

Table 3: Continue

S.E. equation	0.02	0.05	0.05	0.12	0.06	0.40
F-statistic	8.08	3.24	2.18	0.39	2.71	0.84
Log likelihood	79.67	58.71	58.19	30.19	54.7	-8.20
Akaike AIC	-3.98	-2.71	-2.67	-0.98	-2.46	1.34
Schwarz SC	-3.34	-2.07	-2.04	-0.34	-1.83	1.98

Notes: *** , ** and * denote significance at 1%, 5%. and 10% level, respectively

From an estimated VAR, we compute variance decompositions and impulse-response functions, which serve as tools for evaluating the dynamic interactions and strength of causal relations among variables in the system. The results of variance decomposition and impulse response functions are displayed in Table 4 and Figure 1, 2 respectively. From Figure 1The IRF can produce the time path of dependent variables in the VAR, to shocks from all the explanatory variables. The shocks from Government expenditure, ICT and oil revenue to GDP uptrend until third period and then downtrend. Monetary shock from two period until six period uptrend and then downtrend. The shocks of Domestic credit to private sector (% of GDP) as financial shocks (privy) until tow period uptrend and then stable.

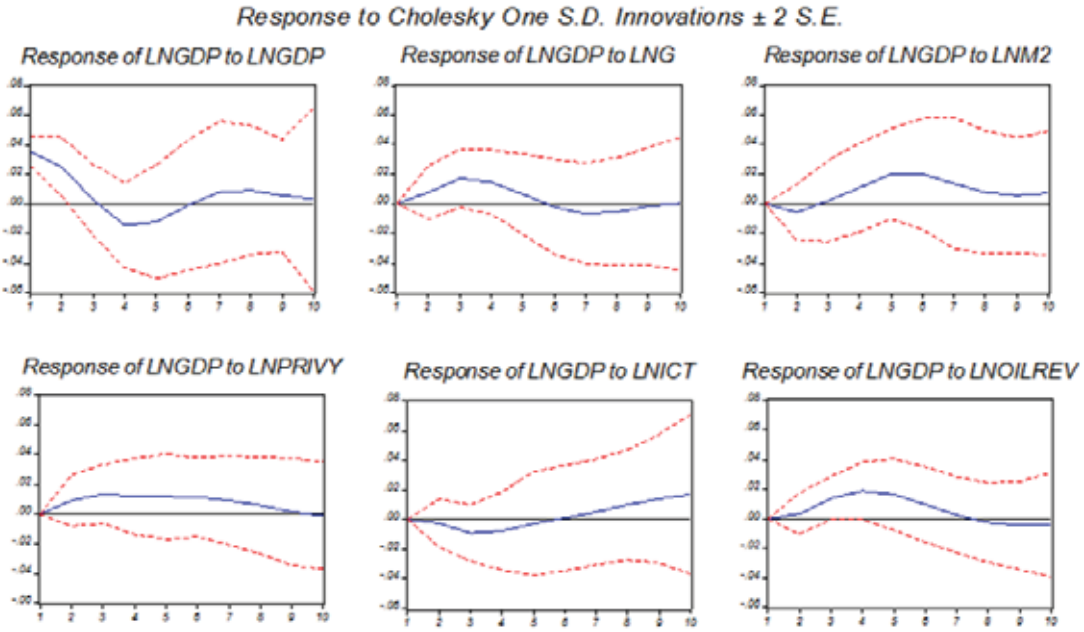

Fig. 1: Impulse Response Functions

As discussed earlier, the variance decomposition is an alternative method to IRF for examining the effects of shocks to the dependent variables. It determines how much of the forecast error variance for any variable in a system is explained by innovations to each explanatory variable, over a series of time horizons. Usually own series shocks explain most of the error variance, although the shock will also affect other variables in the system.

Table 4: Variance Decompositions of lnGDP

period	S.E.	LNGDP	LNG	LNM2	LNPRIVY	LNICT	LNOILREV
1	0.035702	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.045821	90.97697	2.800245	1.424444	3.885701	0.310009	0.602626
3	0.053570	66.83184	12.35608	1.163989	9.226081	3.186505	7.235510
4	0.063003	53.45973	14.33239	3.929582	10.19662	3.776002	14.30568
5	0.070537	45.54720	12.29532	11.21255	10.88394	3.195327	16.86566
6	0.074882	40.42658	10.98571	17.12070	11.96338	2.854775	16.64885
7	0.077611	38.70780	10.92149	19.10954	12.55999	3.098653	15.60253
8	0.079597	38.19466	10.81810	19.13676	12.44486	4.466179	14.93944
9	0.081384	37.04536	10.39013	18.78813	11.94280	7.254315	14.57927
10	0.083617	35.24365	9.842860	18.51852	11.32616	10.97690	14.09190

Overall, results from the analysis clearly prevail the existence of herd behavior among shocks in the short-term Business cycle in Iran's economy. In particular, The result of variance decomposition is shown in Table 4 The demand shock accounts for 40 percent and The supply shock accounts for 25 percent of forecast error variance of GDP**.** Also Figure 2 shows the contributions of fiscal, monetary, financial, ICT and oil shocks to the variances of the forecast errors of output at different horizons.

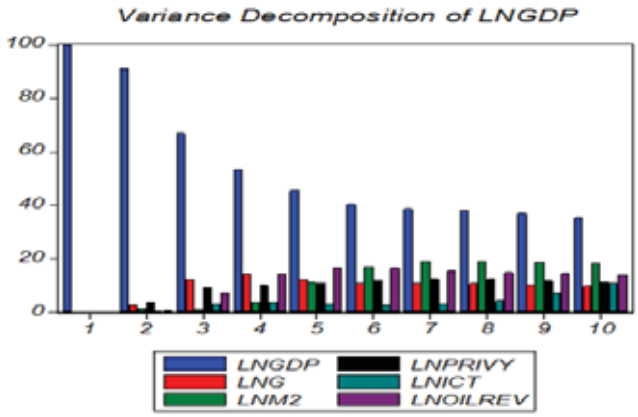

Fig. 2:

The Figure 2 show that GDP to explain instability itself have been maximum amount in length of pried, of course, The role of other variable increase to explain instability of GDP .also monetary variable including currency, have increased the explanatory the best power of the model considerably, and Technology shocks including ICT, have increased the explanatory the less power.

Conclusion:

The motivation to conduct this research was to determine the factors affecting the business cycles in the economy of Iran. For this purpose, a series of variables affecting the business cycles in the economy of Iran were identified and estimated. Based on the obtained results, the variables of government expenditures(G) ,m2, privy, ICT , oil revenue, , all have had a significant effect on the business cycles in Iran at the time period of 1974 to 2008. The set of these variables have explained 65 percent of the growth of the GDP. Introducing the monetary variables including currency, have increased the explanatory feature of the model considerably. However, technology shocks including ICT, have increased the explanatory the less power. Therefore, it is concluded that the factors affecting on the economic fluctuation of Iran in the time period under investigation have been non-monetary factors and supply side parameters.

Using the VECM model to analyze the behavior of shocks on business cycle in Iran economy, the study finds evidence supporting the existence of herd behavior among shocks on business cycle in Iran economy. Impulse response functions are displayed G, ICT and oil revenue shocks to GDP uptrend until third period and then downtrend. Monetary shock from two period until six period uptrend and then downtrend. The shocks of Domestic credit to private sector (% of GDP) as financial shocks (privy) until tow period uptrend and then stable. This finding is further supported by the VDC analysis since a significant proportion of the fluctuations in business cycle in Iran economy.

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