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Original Research Article

The Effectiveness of Regulatory Policies in Curbing the Housing Price in Iran

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In recent years, policymakers have generally relied on regulatory policies to address financial stability concerns. However, our understanding of these policies and their efficacy in curbing housing prices is limited. In this paper, we examine the impact of three regulatory tools, i.e., LTV (loan to value) ratio, reserve requirement rate (RR), and capital adequacy ratio (CAR) on housing price inflation in Iran for 1993: Q2 to 2017:Q1 period. We investigate whether tightening the policy tools are useful in curbing the housing price inflation by using a vector autoregressive model. The results indicate that all three regulatory policy tools exhibit counter-cyclical impact on housing inflation, but with varying degrees of influence. While the impact of CAR tightening in curbing housing prices is quite trivial, the effects of RR and LTV tightening are roughly significant.

Keywords: Regulatory Tools, Housing Prices, Time Series.
JEL Classification*:* C32, F41, F44

1 Introduction

"Many episodes of financial instability and crises have been associated with housing market booms followed by busts. Reinhart and Rogoff show that the six major historical episodes of banking crises in advanced economies since the mid-1970s were all associated with a housing bust (Reinhart, & Rogoff, 2009). They show that this pattern can also be found in many emerging market crises, including the Asian financial crisis of 1997– 98, with the magnitude of house price declines being broadly similar in both advanced and emerging market countries. Since house purchases typically involve household borrowing, house prices are likely to be strongly driven by credit conditions and household leverage" (He & Kang, 2016).

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After the 2007-2008 global crisis, a major priority for policymakers in both advanced and emerging market countries. The purpose of monetary policy is to stabilize prices. Meanwhile, the macroprudential policy is a prudential regulatory instrument that is intended to encourage the stability of the financial system. The macroprudential policy has two dimensions. The first one focuses on the prudential regulation that applies to individual financial institutions towards the regulation of the overall system, and the second is the dimension, which aimed to reduce the risk of excessive procyclicality in the financial system. (Claessens, Ghosh, & Mihet, 2013). The macroprudential policy, together with the monetary policy, works as a counter-cyclical instrument to reduce economic fluctuations (Arnold, Ellis, & Moshirian, 2012; Gersbach, & Rochet, 2012).

For implementing a macroprudential policy, an institutional framework is required. As was mentioned before, there are two kinds of macroprudential tools, sectoral tools used as counter-cyclical tools to curb the excess credit to the housing sector (IMF, 2014a,b). These tools consist of sectoral capital requirements, limits on loan-to-value (LTV) ratios, loan-to-income (LTI) ratios, and caps on debt-service-to-income (DSTI) ratios. These tools can help to increase the resilience of borrowers and the financial system to economic shocks (Cerutti, Claessens, & Laeven, 2017). LTV and DSTI cap by dampening housing credit growth increases the resilience of borrowers to asset price or income shocks (Akinci, & Olmstead-Rumsey, 2018). DSTI or LTI caps can act as automatic stabilizers. These tools, through the house price expectation, can reduce speculative demand for housing (IMF, 2011).

The empirical results about the effectiveness of these tools are mingled. The effectiveness can be accelerated by combining sectoral tools. In the case of house prices, inflation cutting LTV (which cap the size of a housing loan relative to the value of a house) is less effective than the tools which restrict the size of debt service payments to a fixed share of household incomes (DSTI caps). DSTI and LTI caps can also enhance the effectiveness of LTV limits by containing the use of unsecured loans to the household. In a low-interest-rate environment, the DSTI cap limit can complement LTV limits during housing busts, a housing bust causes credit crises and puts downward pressure on housing prices. At the same time, sectoral tools can be eased to prevent more falls in housing prices (IMF, 2011).

The housing prices in Iran had a growing pattern during the period under consideration. The housing price growth in most of the years exceeded the GDP per capita growth. It means that the ability of the household to provide real estate reveals a downward pattern. (Figure 1.)

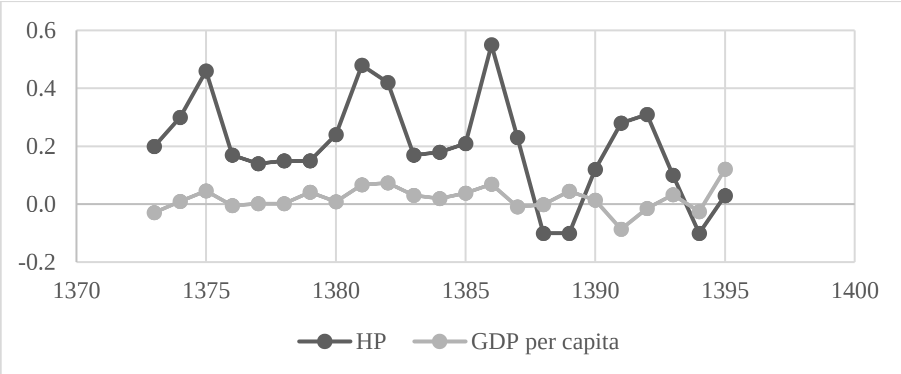

Figure 1. The GDP Per Capita Growth vs. Housing Price Inflation.

Several regulatory policy tools have been practiced in Iran, including: (i) LTV ratio for housing loan (ii) capital adequacy ratio (CAR), and reserve required ratio, RR According to the figure the range of applying the LTV tool was between 70 %(in 2007) and 20 %(in 2000) respectively.

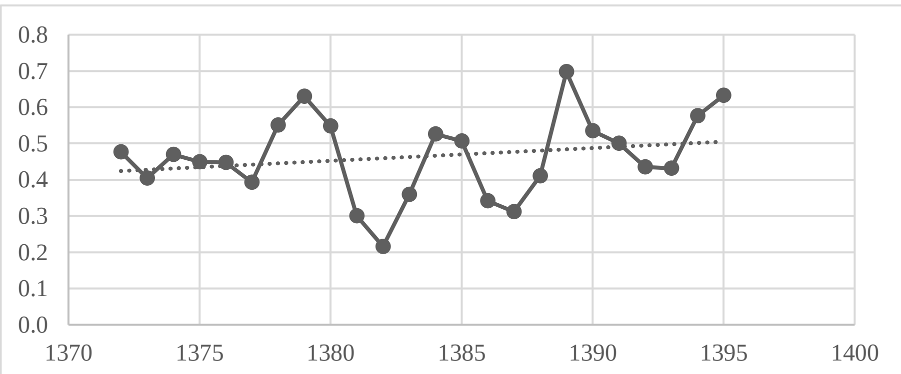

Figure 2. LTV Ratio in Iran.

As Figure 3 shows, the reserve requirement ratio reveals a downward pattern. It fell from 30% in 1992 to 10% in 2017. According to Figure 4, the ratio of capital adequacy of Iranian banks until 2011 satisfied the minimum requirement of 8% assigned by Basel I, but after that, the banks violated the rules.

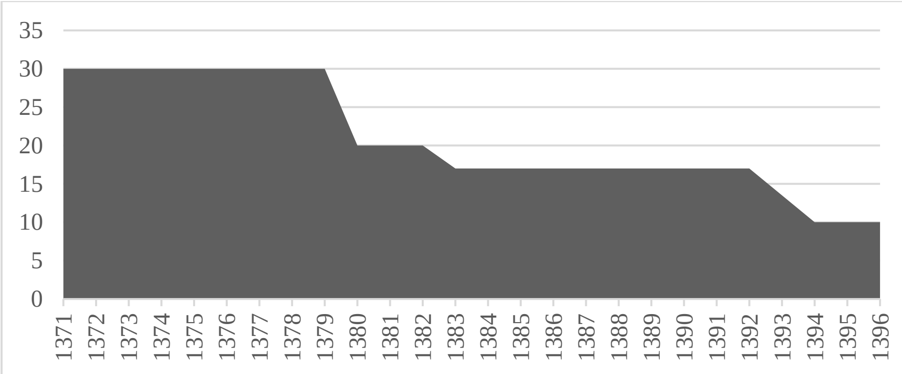

Figure 3. The Reserve Requirement Ratio in Iran.

Figure 4. Capital Adequacy Ratio in Iran.

This paper has attempted to shed light on literature by utilizing the Iranian experience for the 2007-2017 period. By employing the seasonal data, the impact of regulatory policy changes on housing price inflation during the period under consideration was examined. For this purpose, a V.A.R.[1]model is established, which was based on the results of the unit root test and cointegration test. Then it is followed by using the impulse response function (I.R.F.) and variance decomposition (V.D.). In the end, this paper put forward some corresponding policy recommendations to make the housing price steady and healthy.

[1] Vector autoregressive

The rest of the paper is structured as follows—the next section is devoted to the Review of Literature. The method, empirical model, and regression results are discussed in Section 3, while Section 4 concludes the paper.

2 Review of Literature

The empirical results about the effectiveness of the macroprudential tools on the housing market are controversial. The majority of cross country studies by using panel data for different regions suggest that the tools are effective in reducing mortgage credit (Zhang & Zoli, 2016; IMF, 2014a). Furthermore, the evidence from emerging Europe shows that macroprudential tools, especially sectoral housing measures, curtailed the house price growth (Vandenbussche, & Detragiache, 2015; Craig, & Hua, 2011). On the other hand, Kuttner and Shim (2016) find evidence for the impact of DSTI, LTV caps, limits on banks' exposure to the housing market, and housing taxes on house price appreciation. They also find that macroprudential policies, directly targeted borrowers, are less effective than strategies that targeted banks. Europe, by constructing a database of 29 different macroprudential measures aimed at 16 countries in Central, Eastern, and Southeastern. The results reveal that among the 29 policy variables, only four of them have a significant impact on curbing house prices. Cerutti, Claessens, and Laeven (2017), by using 12 different measures of macroprudential policies in 119 countries, finds that in the advanced countries, there is a weak negative correlation among some of the borrower based measures and household credit growth. Still, no correlation between these measures and house prices is found. Akinci and Olmstead-Rumsey (2018), by using a dynamic panel data model, studied the usefulness of these policies in curbing credit growth and house price appreciation in advanced and emerging economies. They showed the macro-prudential policies which have been used after the global financial crisis primarily targeted the housing sector, especially in the advanced economies.

The results imply that macroprudential tightening is associated with lower bank credit growth, housing credit growth, and house price appreciation. The targeted policies which intended to limit house price appreciation were more effective, especially in economies where bank refinance is essential. Afshari and Khezri (2020), construct an index for macroprudential policies for 30 advanced and emerging economies covering the period from 2000: Q1 to 2015: Q4, by using a dynamic panel data model to assess the effectiveness of these policies in curbing housing price appreciation. The results show that only the policies which targeting the housing sector were successful in curbing housing prices. In comparison, other macroprudential policies were not successful in curbing housing price growth. It is noticeable that the interaction of monetary and macroprudential policies was effective in reducing the housing price growth in a panel of selected countries.

Craig and Hua (2011) find that curbs on LTVs and stamp duties on property transactions helped slow down property price inflation in Hong Kong. S.A.R. Wong, Fong, Li, and Choi (2011) propose evidence of LTV effectiveness in reducing failures after property busts in a few Asian economies. Tovar, Garcia-Escribano, and Vera Martin (2012) show that the use of macroprudential instruments such as reserve requirement effectively applied in Brazil and Peru, while in Colombia was not. Igan and Kang (2011) by focusing on 13 interventions, ten tightenings, and loosening of the credit conditions, Six cases were related to LTV and seven to D.T.I. between 2001 and 2009 in Korea. They find that the adoption of LTV and D.T.I. ratios in the second half of the 2000s was successful in slowing down housing price inflation. Claessens, Ghosh, and Mihet (2013) focus on bank risk variables using panel data of 2300 banks from 35 countries. They find that measures targeted the borrowers (LTV and D.T.I. rules) are likely to be effective in reducing the leveraged growth of banks. Bustamante, Gonzales, and Perez (2012) examined the effectiveness of the macroprudential instruments in Colombia. The results suggest that among the applied tools, LTV was the less effective policy.

In general, it seems that the implementation of LTV and D.T.I. limits are occasionally associated with slower credit growth and house price appreciation. As the measures may be implemented in different ways and with varying degrees of intensity in different countries and periods, it is not easy to infer the contradictory results without further information on the details of the measures and housing market conditions. Also, a meaningful comparison of the different measures requires assuming that implementing a given D.T.I. limit is an equally stringent measure as lowering the maximum LTV ratio by a certain amount. Therefore, even with more detailed information on the implementation of the measures, it is not clear how the efficiency of the different types of measures should be compared. Although cross-country studies using aggregate data on credit growth and house prices cannot identify the causal effects of the different types of policy measures, they are useful when building early warning indicators that rely on correlations between the critical variables. Therefore, the mixed results in the effectiveness of the abovementioned tools highly depend on the policy designed and implemented.

3 Methods and Data

3.1 Methods

V.A.R. model is a kind of non-structured equation model which takes each of the endogenous variables in the economic system as a function of the lagged values of all endogenous variables. It is always used to forecast interconnected time-series systems and analyze the dynamic impact of random disturbance on the variable system. Then it could explain the effects of various economic shocks on the formation of economic variables. In the analysis of the V.A.R. model, we often do not analyze the influence of one variable on another variable, but the dynamic impact of variation of error term or external shocks on the variables (Impulse response function method). It can provide information about the positive and negative direction of the response, the adjustment of the time delay, and the stabilization process generated by the impact of the system. Combined with the research of this paper, the result of the impulse response function can describe the dynamic process of housing prices caused by a variable change in housing prices. In the following, we use the V.A.R. model to illustrate the basic idea of the impulse response function. The variance decomposition gives information about the relative importance of each random disturbance to the variables in the system, which can evaluate the significance of the impact of different structures.

3.2 Data

The central hypothesis is that the housing price index is affected, at least temporarily by regulatory policies. For this purpose, the impact of three regulatory tools, i.e., LTV, RR, and CAR on the housing price index, will be investigated. We include several control variables in the model: GDP per capita, working-age population, real policy rate. All the variables are adjusted seasonally for the 1998-2017 period. The descriptive statistics are reported in table 2.

Table 1
List of Variables

Variables	Definitions	Empirical definition	Sources
H	Housing price Index	Log of real Price of one sq meters of housing in major Cities index (2011 base year)	Statistical Center of Iran
LY	Real GDP per capita	Log of Real GDP per capita (2011 base year)	Central Bank of the Islamic Republic of Iran
L.W.P.	The working population	Log of the working population	World Bank
r	Real policy rate	Expected Rates of Return on Facilities Construction and Housing% (2011 base year(	Central Bank of the Islamic Republic of Iran
LTV	Loan to value ratio	Loan-to-value ceiling (in percent) (100 - maximum LTV) / 20	Authors calculation
RR	Required reserve ratio	The minimum amount of reserves that must be held by a commercial.[1]	Central Bank of the Islamic Republic of Iran
CAR	Capital Adequacy Ratio	CAR is calculated by dividing a bank's capital by its risk-weighted assets.	Ramezani & Kordbacheh (2017)

Table 2
Descriptive Statistics

	LY	LWP	r	RR	CAR	LTV
Mean	18.0477	17.6216	-0.03725	0.21104	0.08396	0.46371
Median	18.0923	17.6824	-0.01370	0.18500	0.09000	0.45900
Maximum	18.2716	17.8601	0.09110	0.30000	0.09500	0.69700
Minimum	17.8131	17.2501	-0.31180	0.10000	0.06200	0.21500
Std. Dev.	0.16016	0.20349	0.10681	0.06897	0.01035	0.11480
Skewness	-0.18325	-0.50647	-0.97404	0.24725	-1.11096	-0.05880
Kurtosis	1.43102	1.84671	3.16141	1.73280	2.53055	2.70589
Jarque-Bera	2.59603	2.35613	3.82106	1.85033	5.15734	0.10033
Probability	0.27307	0.30787	0.14800	0.39647	0.07588	0.95107
Sum	433.145	422.918	-0.89410	5.06500	2.01500	11.1290
Sum Sq. Dev.	0.58997	0.95235	0.26241	0.10940	0.00246	0.30310

[1] According to the Monetary and Banking Law of Iran, the CBI is authorized to determine RRR within 10 to 30 percent depending on banks'' liabilities composition and field of activity

For the analysis of the time series of economic variables, first, we should test the stability of the variables. Otherwise, there will be false regression. If the variable is not a stationary time series, we can differentiate the variables until the sequence is stable. If the sequence is steady after n times differentiation, the original sequence is a single integer sequence of order n and is denoted as an I (n). If the ADF statistics is higher than the critical value at the 5% significant level, so we cannot reject the hypothesis that the time series is a non-stationary sequence. According to the results display in table 3, the variables are not integrated in the same order (three-time series are stationary at the level, and the other four are I(1).

Table 3

Augmented Dickey-Fuller Test (A.D.F.) Equation

Variable	A.D.F. statistics	Optimal lags	Critical values 1%	5%	10%	Order of integration
H	-2.7688	3	-2.5906	-1.9444	-1.6144	I(1)
Y	-5.9798	2	-3.5030	-2.8932	-2.5837	I(1)
r	-2.6237	2	-2.5900	-1.9443	-1.6144	I(0)
WP	-7.4475	1	-3.5014	-2.8925	-2.5833	I(0)
LTV	-3.4488	4	-3.5038	-2.8935	-2.5839	I(0)
RR	-6.7453	1	-2.5900	-1.9443	-1.6144	I(1)
CAR	-6.7453	1	-2.5900	-1.9443	-1.6144	I(1)

3.3 Results

We now proceed to identify the lag length of our V.A.R. system, estimate the impulse response functions, and finally analyze the variance decomposition. Tables 4a, 4b, and 4c indicate the suggested lag length based on different criteria: most selection criteria (HQIC[1], SC[2]) support the inclusion of two lags (except for the likelihood-ratio (F.P.E.[3], A.I.C.[4], L.R.[5]) test that is in favor of three lags). We decide on two lags for our V.A.R. estimations. Then, The Johansen test is used to determine whether there is a cointegration relationship among these variables. Table 5a-5c summarizes the results

[1] Hannan-Quinn information criterion
[2] Schwarz information criterion
[3] Final prediction error
[4] Akaike information criterion
[5] sequential modified LR test statistic (each test at 5% level)

Table 4a

V.A.R. Lag Order Selection Criteria (Model 1- LTV)

Lag	Log L	LR	FPE	AIC	SC	HQ
0	562.4632	NA	-3.29e12	-12.25194	-12.11398	-12.19628
1	1247.352	1279.462	-1.65e18	-26.75498	-25.92723	-26.42103
2	1540.694	515.7661	-4.56e21	-32.65261	-31.13506*	-32.04037*
3	1570.267	48.74670*	-4.18e21*	-32.75311*	-30.54576	-31.86259

Table 4b

V.A.R. Lag Order Selection Criteria (model 2- RR)

Lag	Log	LR	FPE	AIC	SC	HQ
0	759.0241	NA	-4.37e14	-16.57196	-16.43400	-16.51630
1	1366.884	1135.562	-1.20e19	-29.38206	-28.55430	-29.04811
2	1663.401	521.3488	-3.08e22	-35.34947	-33.83191*	-34.73723*
3	1690.479	44.63388*	-2.98e22*	-35.39513*	-33.18779	-34.50461

Table 4C

V.A.R. Lag Order Selection Criteria (model 3-CAR)

Lag	Log L	LR	FPE	AIC	SC	HQ
0	875.7076	NA	-3.36e15	-19.13643	-18.99847	-19.08077
1	1489.466	1146.582	-8.08e21	-32.07618	-31.24843	-31.74223
2	1797.853	542.2188	-1.60e23	-38.30447	-36.78691*	-37.69223*
3	1824.071	43.21664*	-1.58e23*	-38.33124*	-36.12389	-37.44071

Table 5a

Unrestricted Cointegration Rank Test (Trace) for LTV

Hypothesized No. of C.E. (s)	Trace statistics			Eigenvalue		
	Test Statistics	Critical Value	Prob	Test Statistics	Critical Value	Prob
0	129.6097	69.81889	0.0000	60.37951	33.87687	0.0000
At most 1	69.23023	47.85613	0.0002	39.21784	27.58434	0.0010
At most 2	30.01239	29.79707	0.0472	14.29550	21.13162	0.3413
At most 3	15.71689	15.49471	0.0463	9.713134	14.26460	0.2315
At most 4	6.003754	3.841466	0.0143	6.003754	3.841466	0.0143

Table 5b
Unrestricted Cointegration Rank Test (Trace) for RR

Hypothesized No. of C.E. (s)	**Trace statistics**			**Eigenvalue**		
	Test Statistics	Critical Value	Prob	Test Statistics	Critical Value	Prob
0	142.1101	69.81889	0.0000	54.23881	33.87687	0.0001
At most 1	87.87134	47.85613	0.0000	35.20404	27.58434	0.0043
At most 2	52.66730	29.79707	0.0000	31.95228	21.13162	0.0010
At most 3	20.71502	15.49471	0.0074	13.94681	14.26460	0.0561
At most 4	6.768209	3.841466	0.0093	6.768209	3.841466	0.0093

Table 5c
Unrestricted Cointegration Rank Test (Trace) for CAR

Hypothesized No. of C.E. (s)	**Trace statistics**			**Eigenvalue**		
	Test Statistics	Critical value	Prob	Critical value	Critical value	Prob
0	141.1819	69.8188	0.0000	53.2980	33.8768	0.0001
At most 1	87.8838	47.8561	0.0000	39.7738	27.5843	0.0009
At most2	48.1099	29.7970	0.0002	28.6154	21.1316	0.0037
At most 3	19.4944	15.4947	0.0118	12.1648	14.2646	0.1046
At most 4	7.3296	3.8414	0.0068	7.3296	3.8414	0.0068

According to the above tables, cointegration vectors are estimated for all three models. But for each model, only one of the vectors is used. Three long-run relationships were found between housing price and the regulatory tools (LTV, RR, and CAR) that are consistent with the theoretical background:

$$\Delta LH_t = 3.002\Delta LY_{t-1} - 0.149\, r_{t-1} + 0.056\, lwp_t - 0.0403\, LTV_t$$
$$\Delta LH_t = 5.999\, \Delta LY_{t-1} - 0.889\, r_{t-1} + 8.966\, lwp_t - 8.964\, \Delta rr_t$$
$$\Delta LH_t = 6.315\, \Delta LY_{t-1} - 0.449\, r_{t-1} + 0.129\, lwp_t - 1.573\, \Delta CAR$$

The results indicate that all three regulatory indicators, as well as the policy rate, exhibit a negative impact on housing prices. However, the GDP per capita and working population were positively affected by housing prices in the period under consideration. The results of the stability test reveal that all the Eigenvalue roots are inside the unit circle; it confirms the stability of the models.

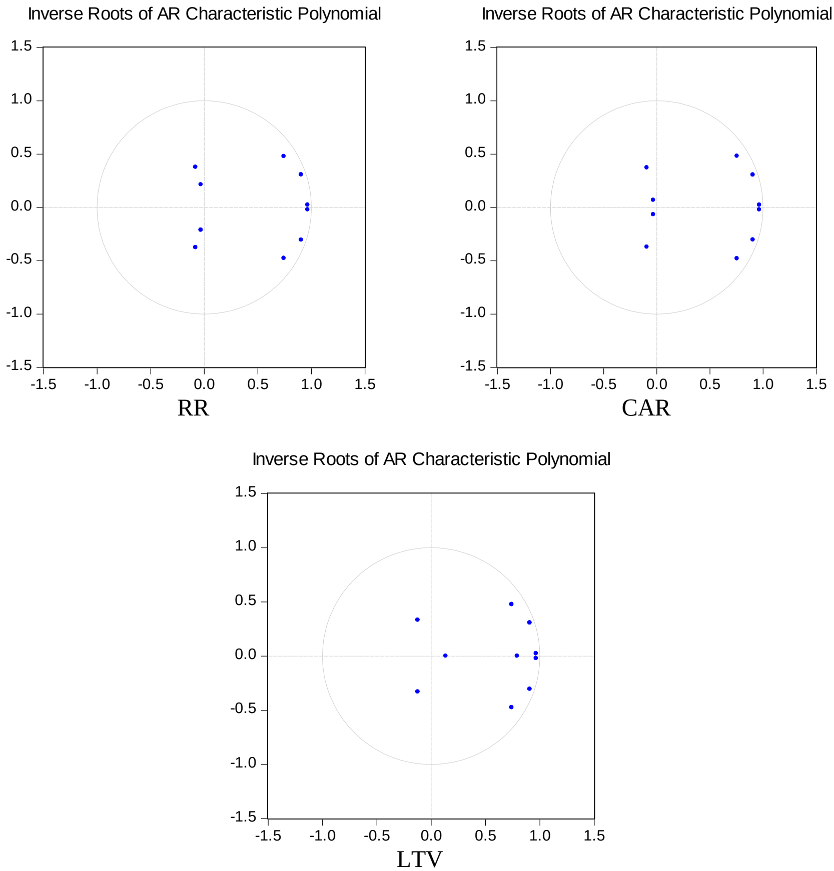

Figure 5. Inverse Roots of Characteristic Polynomial.

We established three V.A.R. models with the time series data of housing prices and selected regulatory policy tools, i.e., LTV, RR, and CAR. EViews 8 was used to estimate the models.

3.4 Impulse Response and Variance Decomposition Analysis

First, we process impulse response functions (I.R.F.s) to trace out the dynamic response of endogenous variables to exogenous shocks arising from other variables. I.R.F.s predict the sign, the magnitude, and the statistical significance of the responses to shocks from policy variables. To analyze the dynamic impact of regulatory measures on housing prices and the contribution of each tool's impact on the change of endogenous variables, the impulse response function, and variance decomposition is depicted.

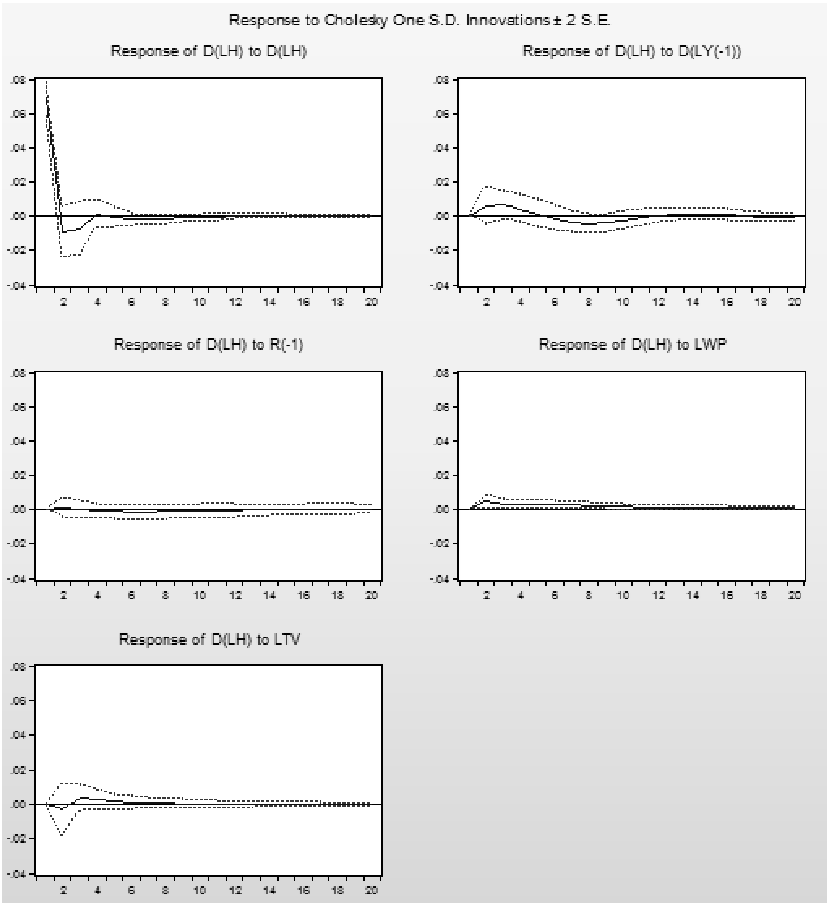

Figure 6a. The Response of Housing Price to LTV Shock.

Figure 6(a) reflects the dynamic response of housing prices, which was shocked by a standard deviation of endogenous variables (LTV): housing prices immediately fall sharply after being hit by a positive shock of LTV, it continued to decrease till the third period. It achieved its maximum value in the third period, then in an oscillatory pattern gradually converge to its long-run value. Therefore, the counter-cyclical impact of LTV only emerged in the short run.

Figure 6(b) displays the dynamic response of housing prices, which was shocked by a standard deviation of the required reserve ratio (RR). The counter-cyclical impact of RR on housing prices emerged after the fourth period, and then in an oscillatory pattern meets its long-run value.

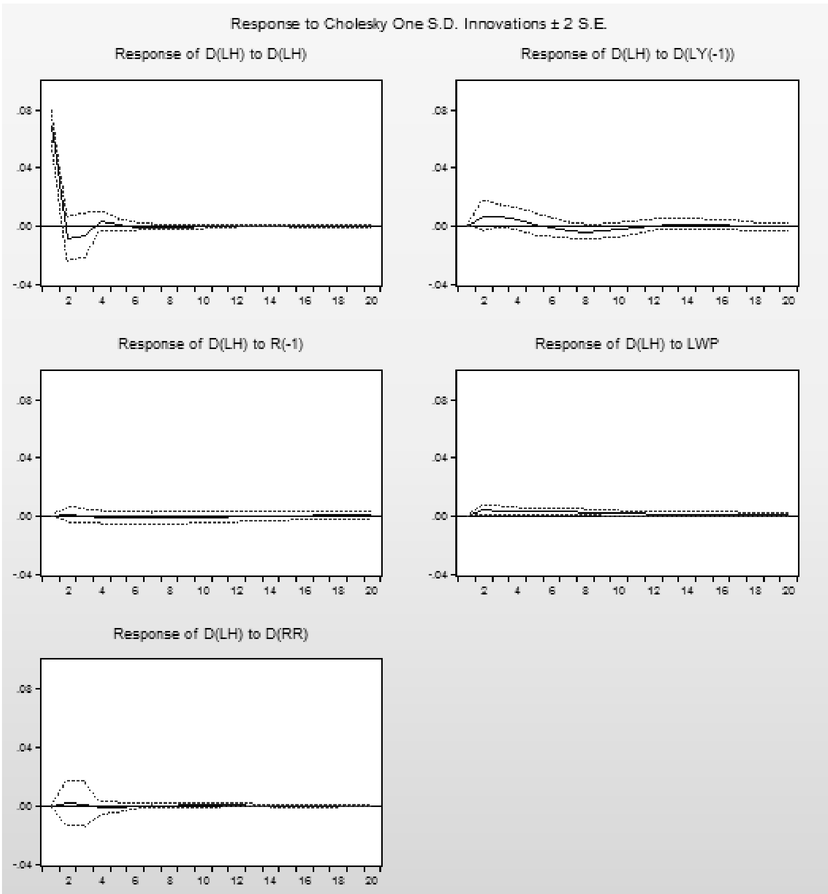

Figure 6(b). The Dynamic Response of Housing Prices to RR Shock.

Figure 6(c) depicts the dynamic response of housing prices to a standard deviation of capital adequacy ratio (CAR). As a result of a tightening CAR, till season 8 the housing price shows an upward pattern, then slightly fell, and finally in an oscillatory pattern gradually converge to its long-run value.

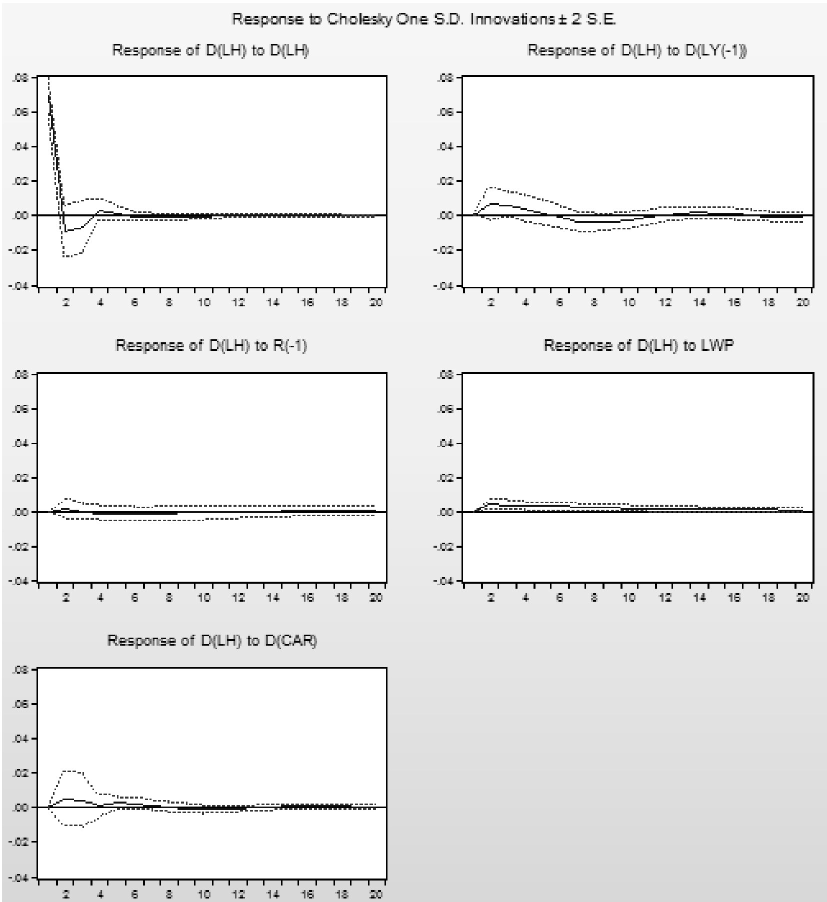

Figure 6(c). The Dynamic Response of Housing Prices to a Standard Deviation of Capital Adequacy Ratio.

In general, the housing prices negatively and with lag respond to the regulatory policy tools in the short run, and an oscillatory pattern converges to its long-run value. The timing and the degree of effectiveness varied with tools. Furthermore, the housing price responds positively to both GDP per capita and working population shocks.

Then, we proceed to decompose the fluctuations of the response variables that arise from these shocks mentioned above in the context of the V.A.R. system. Variance decomposition is used to evaluate the importance of different structural shocks by analyzing the contribution of each structural shock to the change of variables. Variance decomposition results of housing price and regulatory measures are reported in Table 6a, 6b, and6c. The results of the variance decomposition of housing prices reveal that, on average, more than 90% of the changes in housing prices are initiated by themselves. The next two important variables in explaining housing price changes are GDP per capita and working population changes, respectively. It implies that the changes in housing price itself, GDP per capita change, and working population change are respectively the essential variables in explaining the housing price changes.

Table 6a
Variance decomposition-LTV

Period	**S.E.**	**D(LH)**	**D(LY(-1))**	**R(-1)**	**LWP**	**LTV**
1	0.068869	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.070013	98.49312	0.782181	0.033925	0.520757	0.170015
3	0.070839	97.19321	1.556721	0.034075	0.746229	0.469769
4	0.071095	96.52799	1.895114	0.043849	0.936615	0.596435
5	0.071220	96.21960	1.934393	0.067959	1.147623	0.630425
6	0.071344	95.95787	1.959711	0.100433	1.327080	0.654910
7	0.071509	95.56801	2.167504	0.131541	1.467717	0.665225
8	0.071697	95.11333	2.491550	0.154724	1.573731	0.666662
9	0.071844	94.75416	2.758702	0.169605	1.651910	0.665619
10	0.071921	94.56477	2.881237	0.178375	1.710972	0.664646

Table 6b

Variance decomposition-RR

Period	S.E.	D(LH)	D(LY(-1))	R(-1)	LWP	D(RR)
1	0.069293	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.070310	98.64411	0.881230	0.033262	0.370094	0.071303
3	0.070990	97.54928	1.701227	0.032887	0.635791	0.080817
4	0.071286	96.95564	2.001183	0.047479	0.850526	0.145170
5	0.071402	96.65381	2.023033	0.079211	1.071033	0.172914
6	0.071513	96.37075	2.062030	0.122630	1.264268	0.180318
7	0.071675	95.94841	2.288450	0.165208	1.414702	0.183234
8	0.071858	95.47293	2.619151	0.198968	1.526453	0.182501
9	0.072000	95.10616	2.880224	0.222609	1.608416	0.182588
10	0.072075	94.91307	2.994671	0.237837	1.669987	0.184433

Table 6c

Variance decomposition-CAR

Period	S.E.	D(LH)	D(LY(-1))	R(-1)	LWP	D(CAR)
1	0.068907	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.070175	98.092269	0.941474	0.036333	0.368639	0.560866
3	0.070940	96.81849	1.663273	0.035561	0.621930	0.860746
4	0.071216	96.30053	1.954744	0.059685	0.809399	0.875641
5	0.071366	95.91017	1.988560	0.096092	1.001653	1.003527
6	0.071499	95.56485	2.009791	0.137117	1.170554	1.117689
7	0.071648	95.17165	2.203982	0.174021	1.303307	1.147041
8	0.071814	94.73819	2.513499	0.199862	1.404568	1.143878
9	0.071950	94.38671	2.773056	0.215578	1.481253	1.143404
10	0.072029	94.18448	2.893244	0.224755	1.540560	1.156964

The results of variance decomposition revealed that the percentage change of monetary policy variable and all three regulatory tools used in this paper, i.e., LTV, RR, and CAR, were not significant in explaining the housing price changes.

4 Conclusions and Policy Implications

After the 2008–09 global financial crisis, precluding credit and housing price booms has become a significant priority for policymakers. For this purpose, the central banks and regulators started searching for policy instruments beyond those in the standard macroeconomic policy toolkit. Many countries applied non-interest rate policy tools such as maximum LTV, RR, and CAR to curb housing market excesses. But the empirical results reveal ambiguous evidence on the effectiveness of these tools.

This paper, by using Iran's data, tested whether changes in the regulatory policy tools (CAR, RR, and LTV) altered the housing price inflation in the period under consideration. The result of the cointegration test shows that there exists a stable equilibrium relationship between housing prices, regulatory policies, and other variables in the model. The results showed that although all three regulatory policy tools had a counter-cyclical impact on housing prices, its degree and timing were different. While the impact of CAR tightening is oscillatory, the counter-cyclical effect of RR and LTV is substantial. The results of this paper put forward some consistent policy recommendations to make the housing price steady and healthy.

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