Analysis of home sales price in the United States using various micro- and macro-economic variables

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I. INTRODUCTION

The United States is in the midst of a nationwide housing shortage as home prices rise and wages remain stagnant. As of February 2020, at least 29 states in the US have a housing deficit which creates a housing shortage of over 2.5 million units (Khater et al., “The Major Challenge”). This shortage can be attributed to the undersupply of units themselves—caused by several factors including a lack of skilled workers—increasing demand, and unaffordability (Khater et al., “The Housing Supply Shortage”). To that point, in a recent analysis of 473 U.S. counties, the average wage earners in 355 –or 75%– of those counties could not afford the listed median home price in said county (Min, “Average Americans”).

In this paper, I will investigate the effects of various micro- and macro-economic factors on the median home price in the United States. The independent variables that will be investigated are: real gross domestic product per capita, federal interest rates, consumer confidence, unemployment rates, real personal consumption expenditures, and the monthly supply of houses. It is my hypothesis that (1) as real income, consumer confidence, unemployment rate and GDP increase, median housing prices will increase and (2) as federal interest rates decrease, median housing prices will decrease as well.

II. LITERATURE REVIEW

A study conducted by Shanmuga Pillaiyan investigated the macroeconomic drivers of house prices in Malaysia found that real GDP is not a long-term driver of housing prices. This conclusion is in direct opposition of another study on Malaysian housing prices and two other international studies which all found GDP to influence housing prices long-term. Pillaiyan further states that his findings could suggest that “house prices have deviated from economic fundamentals driven by real GDP growth" (125). Additionally, Pullaiyan found that there is no strong relationship between consumer sentiment [confidence] and house prices. Likewise, a study by William Weber and Mike Devaney found that by using the Index of Consumer Sentiment and the Index of Housing Sentiment in tandem, the forecasts of housing starts, or the beginning of new home construction, can be improved upon (344).

Studying the dynamics of metropolitan housing prices, G. Donald Jud and Daniel T. Winkler found that a 1% change in real per capita income is associated with a 0.17% change in real housing prices. Additionally, they found that a 1% change in real, after-tax mortgage interest rates are associated with a 0.024% increase in real housing prices (34).

III. DATA

Economic data was obtained from the Federal Reserve Bank of St. Louis. These data series are time-series datum in quarterly frequency from 1963-2019. The variables used in this investigation are:

Table 1. Variables and their abbreviations.

Variable	Abbreviation
Median sales price of houses sold in the U.S.	MSP
Real gross domestic product per capita	GDP
Real personal consumption expenditures	RPC
Effective federal funds rate	EFF
Unemployment Rate	UNEMP
University of Michigan consumer sentiment	MCS
Monthly supply of houses in the U.S.	MSH

a. Dependent Variable: Median Sales Price of Houses Sold for the United States

Median Sales Price of Houses Sold for the United States (MSP): The median price of houses sold in the United States in U.S. dollars. This variable has been logged and has also been determined to be stationary at the first order of integration (I(1)).

b. Independent Variables:

Real Gross Domestic Product per Capita (GDP): The real gross domestic product per capita in the U.S. This variable assists researchers in gauging how prosperous nations are based upon economic growth. This variable has been logged and has also been determined to be stationary at the first order of integration (I(1)) (Bureau of Economic Analysis).

Real Personal Consumption Expenditures (RPC): A measure of national consumer spending—how much money Americans spend on goods and services. This variable has been logged and has also been determined to be stationary at the first order of integration (I(1)) (Bureau of Economic Analysis).

Effective Federal Funds Rate (EFF): "The rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight" (Board of Governors...). This variable has been determined to be stationary at the first order of integration (I(1)). EFF was originally reported as daily data, but has been transformed to quarterly by taking the simple average of the corresponding daily values in quarterly increments (Board of Governors of the Federal Reserve System).

Unemployment Rate (UNEMP): The number of people who are unemployed as a percentage of the labor force. This variable has been determined to be stationary at the first order of integration

(I(1)). UNEMP was originally reported as monthly data, but has been transformed to quarterly by taking the simple average of the corresponding monthly values in quarterly increments (Bureau of Labor Statistics).

University of Michigan: Consumer Sentiment (MCS): A measure of the overall health of the economy as determined by consumer opinion. This variable has been determined to be stationary at the first order of integration (I(1)). MCS was originally reported as monthly data, but has been transformed to quarterly by taking the simple average of the corresponding monthly values in quarterly increments (University of Michigan).

Monthly Supply of Houses in the United States (MSH): The ratio of houses for sale to houses sold, which provides an indication of the size of the for-sale inventory in relation to the number of houses being sold. This variable has been determined to be stationary at the first order of integration (I(1)). MSH was originally reported as monthly data, but has been transformed to quarterly by taking the simple average of the corresponding monthly values in quarterly increments (U.S. Census Bureau).

Table 2. Summary statistics of non-stationary variables.

Variables	**Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**
GDP	227	38,187.83	11,300.77	19,257	58,167
MSP	227	134,056.80	93,561.98	17,800	337,900
RPC	227	6,812.44	3,271.65	2,206.50	13,353.12
MSH	227	6.071	1.601	3.633	11.4
MCS	227	86.416	12.119	54.367	110.133
UNEMP	227	5.978	1.638	3.4	10.667
EFF	227	5.135	3.698	0.072	17.787

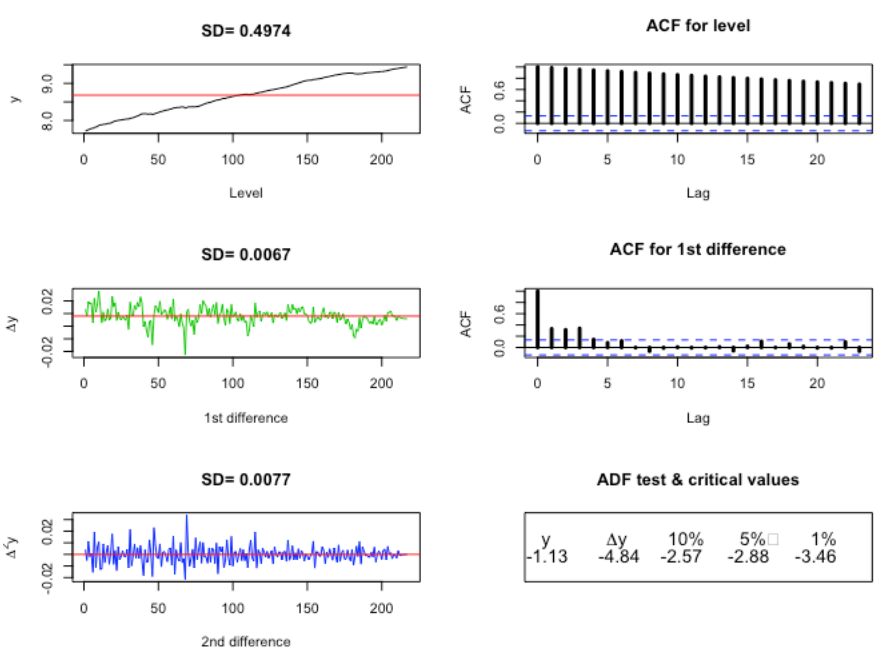
Note: Variables have not been differenced nor logged as presented in the above summary statistics table.

IV. EMPIRICAL METHODOLOGY

a. Determining Stationarity:

Once the logs of GDP, MSP, and RPC have been taken, stationarity of each variable is determined. A stationary time-series variable is one that has a constant mean, variance, and autocorrelation over time. Determining stationarity is determined by the visual observation of the plots for each variable's standard deviation, autocorrelation function (ACF), and augmented Dickey-Fuller test (ADF) between the level variable and its first and second difference. If necessary, stationarity is achieved by differencing variables once for the first order of integration (I(1)), or twice for the second order of integration (I(2)). Each variable in this analysis has been determined to be stationary at the first order of integration (I(1)). An example of this inspection and determination process is below, using RPC as an example of the other variables:

Figure 1. Visual inspection of standard deviation and autocorrelation function of RPC to determine stationarity.



b. Cointegrating Relationships:

The purpose of testing for cointegration is to determine if two or more non-stationary time-series variables move together in the long-run. Two or more variables are cointegrated if 1) there is a linear combination of the variables that are stationary and 2) the variables are nonstationary and integrated of the same order. Two methods to test for cointegrating relationships among variables are the Johansen test and the Engle-Granger method:

1. Johansen tests of cointegration: The two types of Johansen tests of cointegration are the eigenvalue test or the trace test. In either version of the Johansen tests, the null hypothesis is $r = 0$, or no cointegrating relationships; the alternative is $r \geq 1$, implying at least one or more cointegrating relationships.

   Choosing lag length: Lag length is typically chosen by using the VARselect function of R. Total lag order is selected by minimizing each of the four criteria, AIC, HQ, SC, and FPE. As seen from the results inTable 3, a total lag length of 2 has been chosen.

   Table 3. Total lag order results from VARselect.

	AIC	**HQ**	**SC**	**FPE**
Lag length	2	2	1	2

   In both the eigen and the trace tests versions of the Johansen cointegration tests, there is strong evidence of cointegration among the variables as the null hypothesis of no cointegration among the variables is strongly rejected at the one-percent significance level, as signified by the test value being greater than the 1% critical value. These results are evident in Table 4, where the matrix ranks (r), test values, and critical values are visible. Both the Eigen value and trace test indicate a cointegration matrix rank of r = 2.

Table 4. Results of Johansen tests of cointegration.

Test Type		**test**	**10%**	**5%**	**1%**
Eigen	r = 0	162.90	43.25	46.45	51.91
	r <= 1	80.55	37.45	40.30	46.82
	r <= 2	30.13	31.66	34.40	39.79
Trace	r = 0	316.34	126.58	131.7	143.09
	r <= 1	153.44	97.18	102.14	111.01
	r <= 2	72.89	71.86	76.07	84.45

2. Engle-Granger Cointegration Test: The null hypothesis of the Engle-Granger test for cointegration is no cointegration in the time series data. All criteria including visual inspection, standard deviation, ACF, and Augmented Dickey-Fuller tests indicate that the residuals from the cointegrating regression are I(1), which suggests that the variables are not cointegrated—opposing the results of the Johansen tests. This result was checked for robustness by switching the right-hand-side variable for each variable; the same conclusion of no cointegration was made. It is important to note that the results of the Engle-Granger test and the Johansen tests are conflicting. However, it has been stated that the Johansen methods perform better than the Engle-Granger method, primarily due to possible errors carried over in each step and the inability of the Engle-Granger test to detect multiple cointegrating relationships (Bilgili, 1998). Additionally, since this paper is attempting to produce the best possible model for the data, cointegration should be accounted for in the final model. As such, for the remainder of this analysis, cointegration will be accounted for.

c. Model Specification:

1. Dynamic Regression Model

Simple static linear models assume that a dependent variable is only determined by what happens in the current time period--an assumption that does not frequently hold true. To capture dynamic effects of past variables, lagged values of the right-hand-side variables are used in dynamic regression models.

A simplified version of the dynamic regression model for estimating median housing price is as follows, where p indicates the number of lagged time periods:

$$\Delta MSP_t = \alpha + \emptyset_1 \sum_{i=1}^{p_0} \Delta MSP_{t-1} + \beta_1 \sum_{i=0}^{p_1} \Delta GDP_{t-i} + \beta_2 \sum_{i=0}^{p_2} \Delta RPC_{t-1} + \beta_3 \sum_{i=0}^{p_3} \Delta EFF_{t-1}$$

$$+ \beta_4 \sum_{i=0}^{p_4} \Delta MSH_{t-1} + \beta_5 \sum_{i=0}^{p_5} \Delta MCS_{t-1} + \beta_6 \sum_{i=0}^{p_6} \Delta UNEMP_{t-1}$$

$$+ \gamma\ Seasonal\_Dummies + e_t$$

Lag length is chosen by creating different models and removing insignificant lags for each respective variable. In addition to removing insignificant lags, AIC, BIC, root mean squared error are used to determine the best model. The need for seasonal dummies was determined by adding them to the restricted dynamic model and subsequently running an ANOVA test to determine if the unrestricted or restricted model was a better fit ($P < 0.001$). Furthermore, it is necessary to test for serial correlation in the models—when the error terms from different time periods are correlated with each other, leading to smaller standard error than the true standard error—in the dynamic regression models using the Breusch-Godfrey Test. Conducting the Breusch-Godfrey test to the 12th order revealed no serial correlation in the final dynamic regression model ($P > 0.1$), indicating no homoscedastic errors throughout the error term of the final dynamic model.

The best dynamic model (Appendix C.1: Model 2) for this analysis had at least one time-period of significance for each variable, with the largest effects coming from MSP itself and GDP. Additionally, only quarter two was significant in this model.

While dynamic regression models often offer the most simplistic models, they are relatively restrictive as they do not capture long-term effects. Additionally, dynamic regression models are unable to capture the effects of cointegration, which has been proven to be present in this dataset. To capture the effects of cointegration and long-term effects, a VECM model would be the best choice.

2. Auto-Regressive Integrated Moving Average Model (ARIMA)

An ARIMA model, or Auto-Regressive Integrated Moving Average model, is a more generalized regression analysis that aims to predict future data points or better describe the variable of interest. It is important to note that ARIMA models are univariate models, or they only incorporate one focus variable. An ARIMA model has three components: 1) Auto Regressive (AR), where the variable of interest is lagged on its own prior values, 2) Integrated (I), which is representative of the differencing of the raw data that takes place to make the data stationary, 3) Moving Average (MA), where past forecasting errors are of the variable of interest are incorporated (Hyndman & Athanasopoulos, 2018).

The typical form of an ARIMA model is formatted as ARIMA(p,d,q), where p is the lag order or number of lags observed in the model, in AR(p); where d is the number of differences taken of the raw observations (the "I" part of ARIMA); and where q is the order of the moving average, in MA(q).

As median sales price (MSP) has already been determined above to be stationary at I(1), $d = 1$ for all attempted ARIMA models. Several variations of the ARIMA model were attempted with varying values for both p and q. The generalized ARIMA model is as follows:

$$\Delta MSP_t(p,d,q) = \varsigma + \emptyset_p \sum_{i=1}^{p} \Delta MSP_{t-1} + \theta_q \sum_{i=1}^{q} e_{t-1} + e_t$$

The best ARIMA model was chosen to be model 6 (ARIMA(1,1,2)), based upon criteria such as BIC, AIC, and root mean squared percent error, these values are presented below in Table 5.

Table 5. ARIMA model selection criteria.

Model	p	d	q	AIC	BIC	RMSPE
1	0	1	0	-891.52	-888.13	0.002145
2	0	1	1	-889.64	-882.87	0.002141
3	0	1	2	-897.61	-887.46	0.002079
4	1	1	0	-889.70	-882.93	0.002138
5	1	1	1	-927.34	-917.18	0.004251
6	1	1	2	-940.14	-926.60	0.003545
7	2	1	0	-901.50	-891.34	0.002066
8	2	1	1	-937.09	-923.55	0.003890
9	2	1	2	-938.15	-921.23	0.003536

While model six has the lowest AIC and BIC, it does not have the lowest RMSPE. However, RMSPE is influenced by the lag length, so it is not always the best model selection criteria. A graph of the actual values of MSP versus the values of MSP as predicted by the ARIMA(1,1,2) model is located in Appendix D.3.

3. Vector Error Correction Model (VECM)

A vector error correction model (VAR) is typically used to outline the relationship among stationary variables. However, since the data used in this analysis has cointegrating relationships (as determined above) and is not stationary at I(0), a vector error correction model (VECM) is used.

As determined in the Johansen cointegration test, a lag order of 2 will be used in the VEC model specifications (K=2). There are seven VECM models, one for each variable on the right-hand side, which are:

$$\Delta MSP_t = a_1 + \psi_1 \Delta msp_{t-1} + \psi_2 \Delta msp_{t-2} + \psi_3 \Delta gdp_{t-1} + \psi_4 \Delta gdp_{t-2} + \psi_5 \Delta rpc_{t-1} + \psi_6 \Delta rpc_{t-2} + \psi_7 \Delta msh_{t-1} + \psi_8 \Delta \mathrm{msh}_{t-2} + \psi_9 \Delta eff_{t-1} + \psi_{10} \Delta eff_{t-2} + \psi_{11} \Delta unemp_{t-1} + \psi_{12} \Delta unemp_{t-2} + \psi_{13} \Delta mcs_{t-1} + \psi_{14} \Delta mcs_{t-2} + \aleph_1 ecm_{t-1} + u_1$$

$$\Delta GDP_t = a_2 + \gamma_1 \Delta gdp_{t-1} + \gamma_2 \Delta gdp_{t-2} + \gamma_3 \Delta msp_{t-1} + \gamma_4 \Delta msp_{t-2} + \gamma_5 \Delta rpc_{t-1} + \gamma_6 \Delta rpc_{t-2} + \gamma_7 \Delta msh_{t-1} + \gamma_8 \Delta \mathrm{msh}_{t-2} + \gamma_9 \Delta eff_{t-1} + \gamma_{10} \Delta eff_{t-2} + \gamma_{11} \Delta unemp_{t-1} + \gamma_{12} \Delta unemp_{t-2} + \gamma_{13} \Delta mcs_{t-1} + \gamma_{14} \Delta mcs_{t-2} + \aleph_2 ecm_{t-1} + u_2$$

$$\Delta RPC_t = a_3 + \Pi_1 \Delta rpc_{t-1} + \Pi_2 \Delta rpc_{t-2} + \Pi_3 \Delta msp_{t-1} + \Pi_4 \Delta msp_{t-2} + \Pi_5 \Delta gdp_{t-1} + \Pi_6 \Delta gdp_{t-2} + \Pi_7 \Delta msh_{t-1} + \Pi_8 \Delta \mathrm{msh}_{t-2} + \Pi_9 \Delta eff_{t-1} + \Pi_{10} \Delta eff_{t-2} + \Pi_{11} \Delta unemp_{t-1} + \Pi_{12} \Delta unemp_{t-2} + \Pi_{13} \Delta mcs_{t-1} + \Pi_{14} \Delta mcs_{t-2} + \aleph_3 ecm_{t-1} + u_3$$

$$\Delta EFF_t = a_4 + \varrho_1 \Delta eff_{t-1} + \varrho_2 \Delta eff_{t-2} + \varrho_3 \Delta msp_{t-1} + \varrho_4 \Delta msp_{t-2} + \varrho_5 \Delta gdp_{t-1} + \varrho_6 \Delta gdp_{t-2} + \varrho_7 \Delta msh_{t-1} + \varrho_8 \Delta \mathrm{msh}_{t-2} + \varrho_9 \Delta rpc_{t-1} + \varrho_{10} \Delta rpc_{t-2} + \varrho_{11} \Delta unemp_{t-1} + \varrho_{12} \Delta unemp_{t-2} + \varrho_{13} \Delta mcs_{t-1} + \varrho_{14} \Delta mcs_{t-2} + \aleph_4 ecm_{t-1} + u_4$$

$$\Delta MSH_t = a_5 + \lambda_1 \Delta msh_{t-1} + \lambda_2 \Delta msh_{t-2} + \lambda_3 \Delta msp_{t-1} + \lambda_4 \Delta msp_{t-2} + \lambda_5 \Delta gdp_{t-1} + \lambda_6 \Delta gdp_{t-2} + \lambda_7 \Delta eff_{t-1} + \lambda_8 \Delta eff_{t-2} + \lambda_9 \Delta rpc_{t-1} + \lambda_{10} \Delta rpc_{t-2} + \lambda_{11} \Delta unemp_{t-1} + \lambda_{12} \Delta unemp_{t-2} + \lambda_{13} \Delta mcs_{t-1} + \lambda_{14} \Delta mcs_{t-2} + \aleph_5 ecm_{t-1} + u_5$$

$$\Delta MCS_t = a_6 + \rho_1 \Delta mcs_{t-1} + \rho_2 \Delta mcs_{t-2} + \rho_3 \Delta msp_{t-1} + \rho_4 \Delta msp_{t-2} + \rho_5 \Delta gdp_{t-1} + \rho_6 \Delta gdp_{t-2} + \rho_7 \Delta eff_{t-1} + \rho_8 \Delta eff_{t-2} + \rho_9 \Delta rpc_{t-1} + \rho_{10} \Delta rpc_{t-2} + \rho_{11} \Delta unemp_{t-1} + \rho_{12} \Delta unemp_{t-2} + \rho_{13} \Delta msh_{t-1} + \rho_{14} \Delta msh_{t-2} + \aleph_6 ecm_{t-1} + u_6$$

$$\Delta UNEMP_t = a_7 + \mathrm{K}_1 \Delta unemp_{t-1} + \mathrm{K}_2 \Delta unemp_{t-2} + \mathrm{K}_3 \Delta msp_{t-1} + \mathrm{K}_4 \Delta msp_{t-2} + \mathrm{K}_5 \Delta gdp_{t-1} + \mathrm{K}_6 \Delta gdp_{t-2} + \mathrm{K}_7 \Delta eff_{t-1} + \mathrm{K}_8 \Delta eff_{t-2} + \mathrm{K}_9 \Delta rpc_{t-1} + \mathrm{K}_{10} \Delta rpc_{t-2} + \mathrm{K}_{11} \Delta mcs_{t-1} + \mathrm{K}_{12} \Delta mcs_{t-2} + \mathrm{K}_{13} \Delta msh_{t-1} + \mathrm{K}_{14} \Delta msh_{t-2} + \aleph_7 ecm_{t-1} + u_7$$

As evident in Table 6, the p-values of all error correction term models are significant.

Table 6. Descriptive statics of VECM models.

LHS Variable	Model	Residual Standard Error	Adjusted R Square	F-Stat	P-value
t_msp	1	0.0267	0.9991	1.73E+04	<.0001
t_gdp	2	0.006246	0.9996	3.85E+04	<.0001
t_rpc	3	0.005111	0.9999	1.59E+05	<.0001
t_eff	4	0.8008	0.9534	328.2	<.0001
t_msh	5	0.5214	0.8948	137.1	<.0001
t_mcs	6	4.512	0.8619	100.8	<.0001
t_unemp	7	0.2047	0.9845	1019	<.0001

Impulse response functions (IRF) represent the response of one variable given an impulse—or often standard deviation "shock"—in another variable. The impulse response is the derivative of one of the endogenous variables with respect to the error term or shock. Examining the impulse response functions of explanatory variables of on MSP: a positive shock from GDP will have a positive impact to MSP in the short-run and the long-run (E.2.A); a positive shock from RPC will have a positive impact on MSP in the short-run and a relatively neutral impact in the long-run (E.2.B); a positive shock from EFF has a negative impact on MSP in the short-run and a positive impact in the long-run (E.2.C); a positive shock from MSH will have a negative impact on MSP in the short-run and long-run (E.2.D); a positive shock from MCS will have a negative impact on MSP in the short-run and long-run (E.2.E); a positive shock from UNEMP will have a immediately negative impact on MSP in the short-run and a positive impact on MSP in the long-run (E.2.F).

V. CONCLUSION

Of the three models created in this analysis, the vector error correction model (VECM) would be the model that is best suited for forecasting and causal analysis, rather than the dynamic (DYNLM) or the ARIMA model. The reasons for this conclusion are: 1) the data is cointegrated (r =2) and to correct for this cointegration, an error term must be accounted for as is done in the VECM model, 2) long-term effects are often times not represented in simple dynamic models, 3) ARIMA models are focused only on the focus variable itself.

The majority of the conclusions reached through this analysis are done through the interpretations of the IRFs as above and as follows. As one would suspect, most of the IRF interpretations are logical per economic theory as: an increased gross domestic product typically signifies better economic conditions and likely more consumer willingness to spend; an increased personal consumption represents consumers spending more; an increase in housing supply will lead to a decrease in price as a result of simple supply and demand theory. Additionally, the response of MSP to a shock in unemployment is logical as increased unemployment would immediately result in a decreased amount of people willing to spend more on housing, however, in the long-term people would have either re-entered the workforce or wealthier individuals would be willing to spend more on a house.

However, the IRFs of MSP in response to consumer sentiment and effective federal funds rate are in defiance of what would be concluded by simple economic theory or logical deduction. One would expect home prices to increase as consumer confidence increases, while home prices would decrease in response to decreasing federal interest rates. It is important to note that as stated in literature review, previous research has concluded that consumer confidence is not a good indicator of home prices.

References

Board of Governors of the Federal Reserve System (US), Effective Federal Funds Rate [DFF], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DFF, June 1, 2020.

Bilgili, Faik. “Stationarity and Cointegration Tests: Comparison of Engle - Granger and Johansen Methodologies.” *Munich Personal RePEc Archive*, 4 Jan. 2017, mpra.ub.uni-muenchen.de/75967/1/MPRA_paper_75967.pdf.

Hyndman, R.J. & Athanasopoulos, G. (2018). *Forecasting: principles and practice,* 2nd edition, OTexts: Melbourne, Austrailia. OTexts.com/fpp2. Accessed on 6 July 2020.

Jud, G. Donald, and Daniel T Winkler. “The Dynamics of Metropolitan Housing Prices.” *The Journal of Real Estate Research*, vol. 23, no. 1/2, 2002, pp. 29–46., https://www.jstor.org/stable/10.2307/24887611.

Khater, Sam, et al. “The Major Challenge of Inadequate U.S. Housing Supply.” *FreddieMac*, 5 Dec. 2018,www.freddiemac.com/research/insight/20181205_major_challenge_to_u.s._housing_supply.page?

Khater, Sam, et al. “The Housing Supply Shortage: State of the States.” *FreddieMac*, 27 Feb. 2020, www.freddiemac.com/research/insight/20200227-the-housing-supply-shortage.page.

Min, Sarah. “Average Americans Can't Afford a Home in 70 Percent of the Country.” *CSB News*, 28 Mar. 2019, www.cbsnews.com/news/housing-market-2019-americans-cant-afford-a-home-in-70-percent-of-the-country/.

Pillaiyan, Shanmuga. “Macroeconomic Drivers of House Prices in Malaysia.” *Canadian Social Science*, vol. 11, no. 9, 26 Sept. 2015, pp. 119–130., doi:10.3968/7482.

University of Michigan, University of Michigan: Consumer Sentiment [UMCSENT], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UMCSENT, May 30, 2020.

U.S. Bureau of Economic Analysis, Real gross domestic product per capita [A939RX0Q048SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A939RX0Q048SBEA, May 30, 2020.

U.S. Bureau of Economic Analysis, Real Personal Consumption Expenditures [PCECC96], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PCECC96, June 1, 2020.

U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, June 1, 2020.

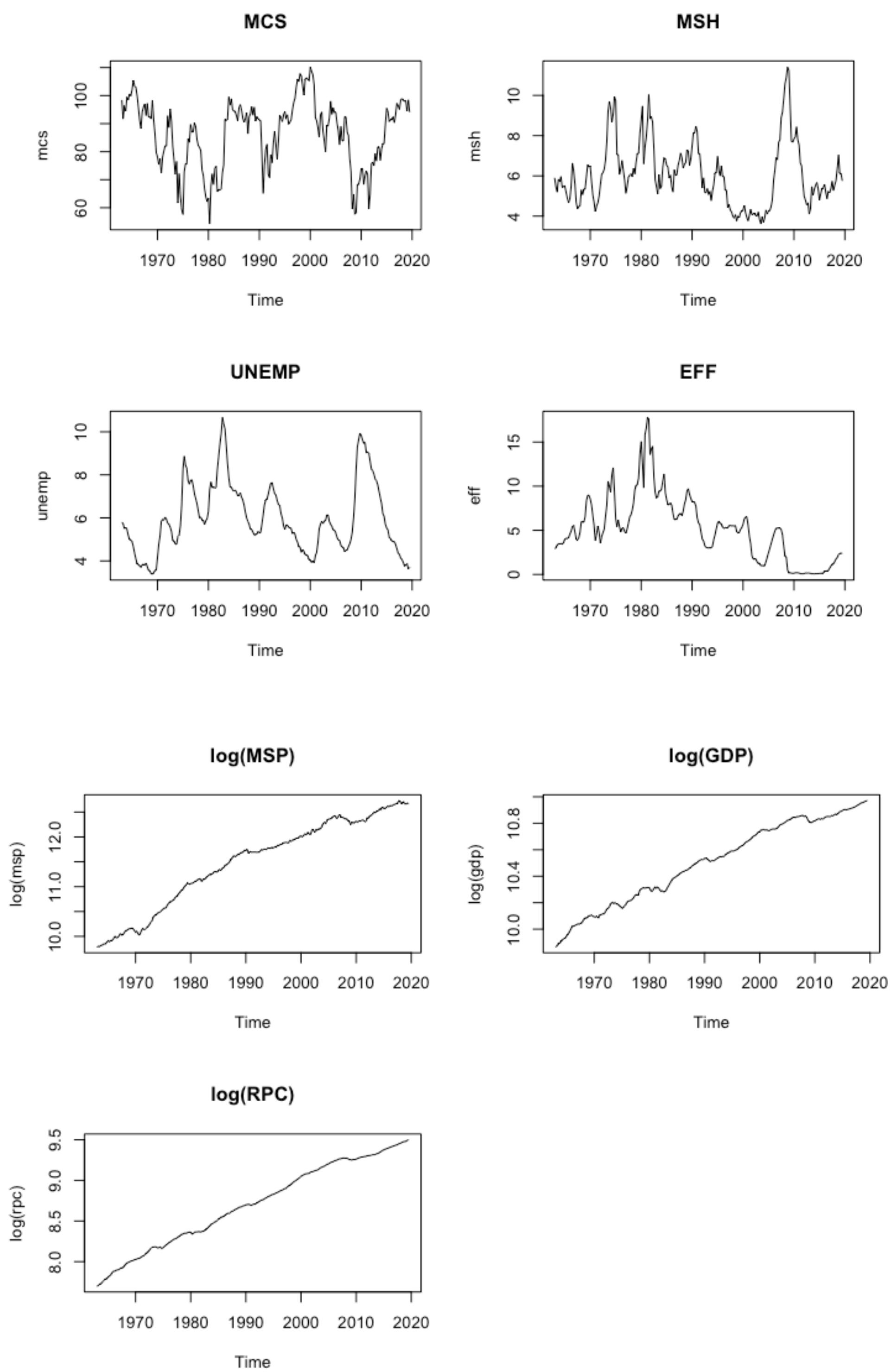
U.S. Census Bureau and U.S. Department of Housing and Urban Development, Median Sales Price of Houses Sold for the United States [MSPUS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MSPUS, June 1, 2020.

U.S. Census Bureau and U.S. Department of Housing and Urban Development, Monthly Supply of Houses in the United States [MSACSR], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MSACSR, July 9, 2020.

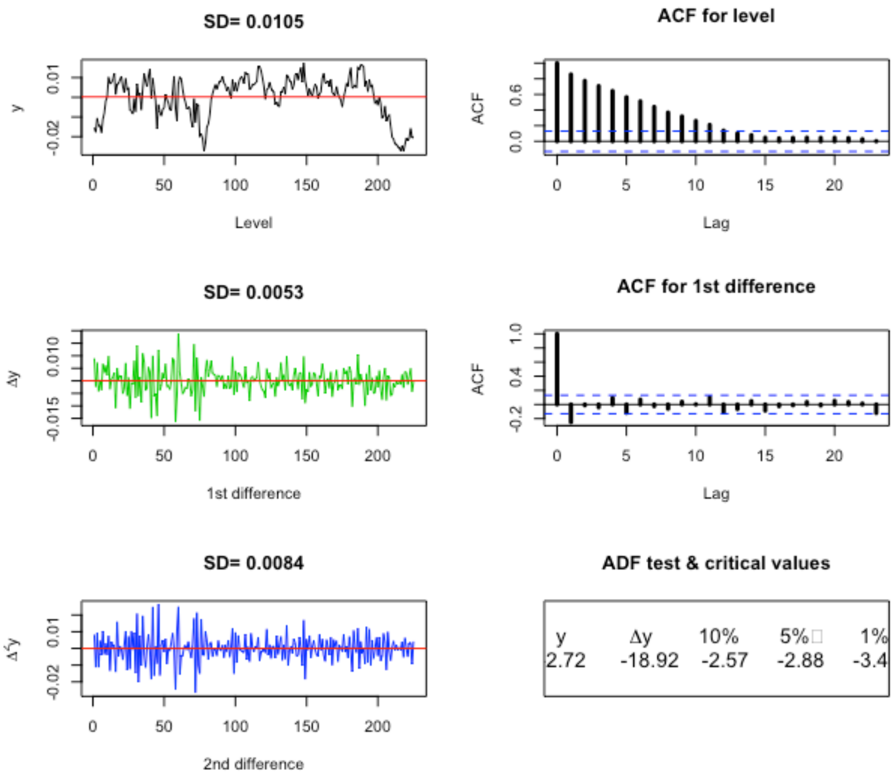
Weber, William, and Mike Devaney. “Can Consumer Sentiment Surveys Forecast Housing Starts?” *The Appraisal Journal*, vol. 64, no. 4, Oct. 1996, pp. 343–348.

APPENDIX

A. Plotted Variables (Pre-Differencing; msp, gdp, and rpc log transformed)



B. Results of Engle-Granger Cointegration Test



C. Dynamic Model Criteria

1. Model (1) restricted (no seasonal dummies); Model (2) unrestricted (with seasonal dummies)

Dynamic Model Comparison

	Dependent variable:	
	tmsp	
	Model (1)	Model (2)
L(tmsp, 1:6)1	-0.330***	-0.275***
	(0.068)	(0.068)
L(tmsp, 1:6)2	-0.040	-0.024
	(0.069)	(0.068)
L(tmsp, 1:6)3	0.190***	0.224***
	(0.064)	(0.065)
L(tmsp, 1:6)4	0.255***	0.165**
	(0.066)	(0.067)
L(tmsp, 1:6)5	0.141**	0.150**
	(0.069)	(0.069)
L(tmsp, 1:6)6	0.100	0.086
	(0.068)	(0.069)
L(tgdp, 1)	0.866***	0.865***
	(0.247)	(0.237)
L(trpc, 8:11)8	-0.578*	-0.386
	(0.313)	(0.305)
L(trpc, 8:11)9	0.603**	0.512*
	(0.301)	(0.292)
L(trpc, 8:11)10	-0.426	-0.358
	(0.300)	(0.290)
L(trpc, 8:11)11	0.790**	0.624**
	(0.319)	(0.310)
L(tmcs, 0)	0.001***	0.001***
	(0.0004)	(0.0003)
L(tmsh, 3)	-0.007**	-0.007**
	(0.003)	(0.003)
L(tunemp, 5:6)5	0.017**	0.016**
	(0.008)	(0.007)

L(tunemp, 5:6)6	-0.015*	-0.014**
	(0.007)	(0.007)
L(teff, 10)	-0.006***	-0.006**
	(0.002)	(0.002)
season(tmsp)Q2		-0.021***
		(0.005)
season(tmsp)Q3		-0.002
		(0.005)
season(tmsp)Q4		-0.006
		(0.005)
Constant	0.002	0.009*
	(0.004)	(0.005)
Observations	207	207
R^2	0.317	0.382
Adjusted R^2	0.259	0.319
Residual Std. Error	0.025 (df = 190)	0.024 (df = 187)
F Statistic	5.507*** (df = 16; 190)	6.073*** (df = 19; 187)
Note:		*p**p***p<0.01

2. ANOVA-Test of Restricted vs Unrestricted

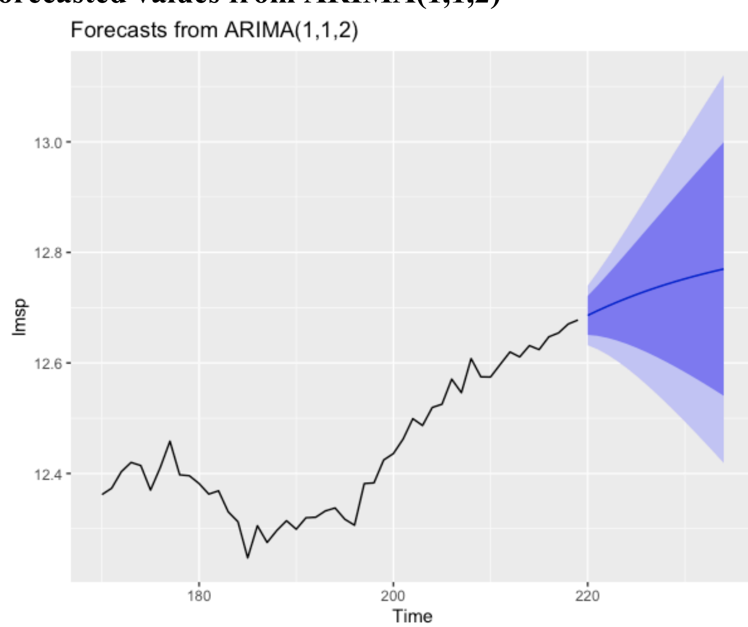
```
Analysis of Variance Table

Model 1: tmsp ~ L(tmsp, 1:6) + L(tgdp, 1) + L(trpc, 8:11) + L(tmcs, 0) +
    L(tmsh, 3) + L(tunemp, 5:6) + L(teff, 10)
Model 2: tmsp ~ L(tmsp, 1:6) + L(tgdp, 1) + L(trpc, 8:11) + L(tmcs, 0) +
    L(tmsh, 3) + L(tunemp, 5:6) + L(teff, 10) + season(tmsp)
  Res.Df     RSS Df Sum of Sq      F    Pr(>F)
1    190 0.11627
2    187 0.10525  3  0.011021 6.5272 0.0003196 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

D. ARIMA Model Criteria

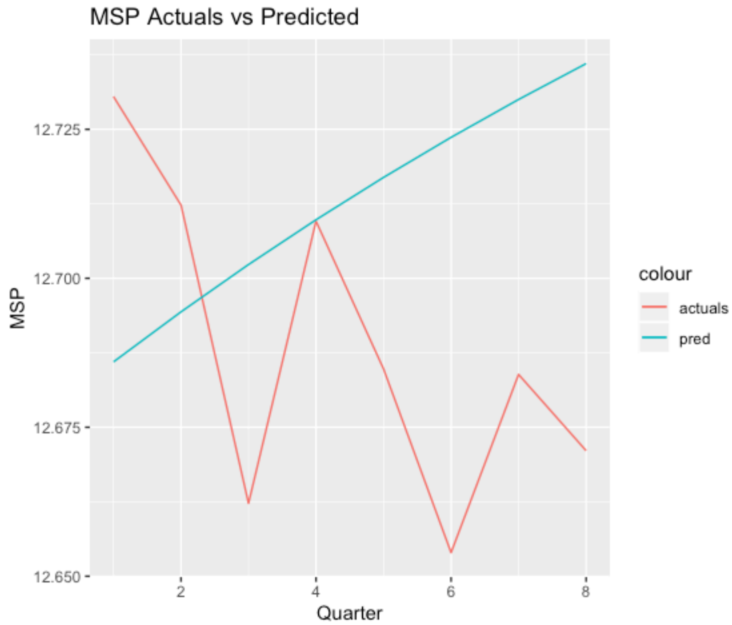
1. ARIMA(1,1,2) Results:

ARIMA(x = lmsp, order = c(1, 1, 2))			
Coefficients:			
	AR(1)	MA(1)	MA(2)
	0.9459	-1.1329	0.3367
s.e.	0.0335	0.067	0.0693
sigma^2 estimated as:	0.0007534		
log likelihood:	474.07		
AIC:	-940.14		
Training set error measures:			
MAE	0.00366724		
RMSE	0.02739379		
MAE	0.02064271		
MPE	0.0331572		
MAPE	0.1819294		
MASE	0.8394293		
ACF1	-0.0155305		

2. Graph of forecasted values from ARIMA(1,1,2)



3. Graph of actual values versus forecasted ARIMA(1,1,2) values



Note: Y-axis range is less than 0.1

E. VAR Model Criteria:

1. VAR Estimation Results:

=========================

Endogenous variables: t_msp, t_gdp, t_rpc, t_eff, t_msh, t_mcs, t_unemp

Deterministic variables: const

Sample size: 225

Log Likelihood: 1308.693

Roots of the characteristic polynomial:

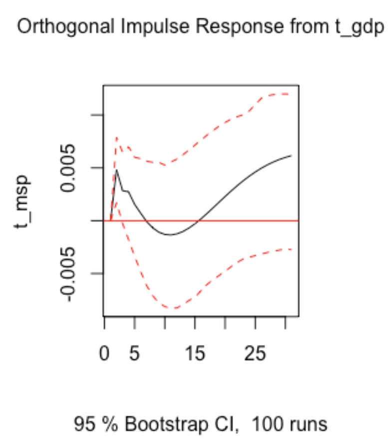
0.9972 0.9815 0.9447 0.9003 0.8952 0.8952 0.8517 0.5227 0.3083 0.2283 0.2283 0.2002 0.1552 0.1552

Call:

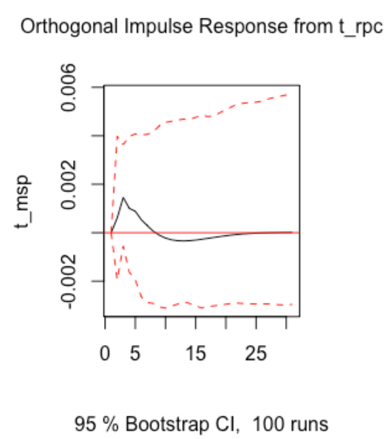
VAR(y = VAR_data, p = 2)

2. Impulse response functions: Explanatory variables' impact on MSP

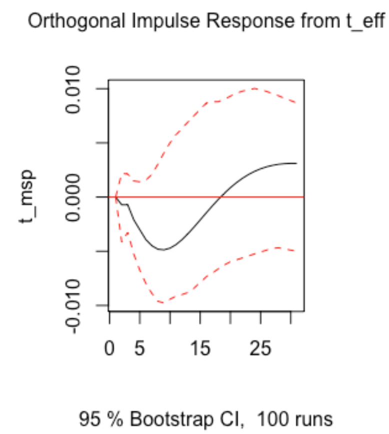
A



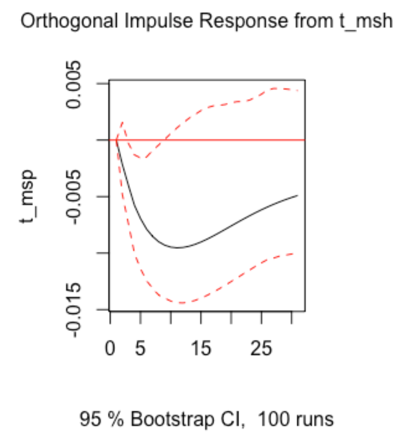
B



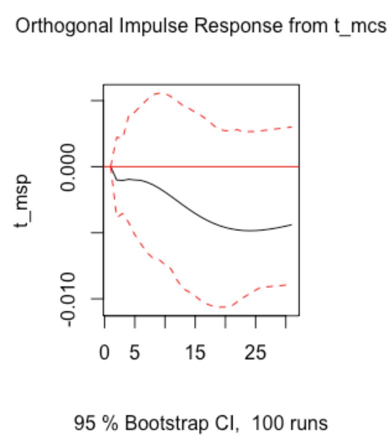
C


Orthogonal Impulse Response from t_eff
t_msp
0.010
0.000
-0.010
0
5
15
25
95 % Bootstrap CI, 100 runs

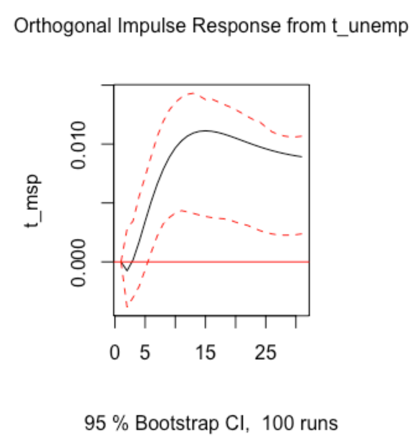
D


Orthogonal Impulse Response from t_msh
t_msp
0.005
-0.005
-0.015
0
5
15
25
95 % Bootstrap CI, 100 runs

E


Orthogonal Impulse Response from t_mcs
t_msp
0.000
-0.010
0
5
15
25
95 % Bootstrap CI, 100 runs

F


Orthogonal Impulse Response from t_unemp
t_msp
0.010
0.000
0
5
15
25
95 % Bootstrap CI, 100 runs