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Does income or house price lead in the public housing market? a case study of Singapore's public housing sector.

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Abstract

The purpose of this study is to find the Granger-causal relationship between house price and income. Singapore is taken as a case study and standard time-series approach is employed. The outcome of this relationship will determine the lead-lag relation between house price and income which will then provide some policy implications to tackle the rising housing price and income distribution as well as housing affordability in Singapore. However, the empirical findings based on the generalised VDC (forecast variance decompositions) tend to indicate that unemployment rate is the most lagging factor, while house price is the most leading variable followed by the income variable. This happens due to the probability that house price is controlled and determined by HDB (Housing Development Board), the government entity for public housing in Singapore. This has strong policy implications.

Key words:

HDB, CPI, GDP, House price, cointegration, unemployment, Singapore

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Introduction

There are quite a number of literatures studying on the relationship between house price and income to find which is leading and which is lagging. Some literatures have found significant results while some found it to be inconclusive and some found it to be insignificant. It is not impossible to have such kind of results due to the nature of the study based on different geographical locations and policies. Choices of variables chosen are based on literatures relating to house prices and income. In this study, in addition to house prices and income, three more variables are added as explanatory variables, namely, GDP as proxy to economic growth, CPI as proxy to inflation and unemployment rate. As a conclusion, HDB resale price index is found to be the leading variable (exogenous) followed by disposable income, GDP, CPI and followed by unemployment rate. It contradicts with VECM model where HDB resale price index found to be endogenous at 5% significance level.

In comparison to other housing markets, Singapore is unique due to its limited land for housing. Singapore is a small densely populated Island city state³ with current population of around 5.7 million and will be seeing an increase to this population growth. In Singapore, most of the people usually go for public housing which is built-to-order (BTO) by the Housing Development Board (HDB) for new home owners due to its affordability compared to private housing both landed and non-landed such as condo apartments which is more expensive afforded by the higher income earners. Commonly it is known as HDB flats which can be purchased directly from HDB or from other owners of the HDB flats which is then referred as resale flats at market price through house agents. Owners of HDB flats can only sell back the flat after five years which is the minimum of occupancy period (MOP) and is subjected to Ethnic Integration Policy (EIP) quota to ensure a balanced ethnic mix in HDB estates, thereby promoting racial integration and harmony.⁴

The affordability of owning an HDB flat is made as such that the owners are able to pay through CPF (Central Provident Fund), a mandatory national-savings scheme into which most citizens are required to deduct from their monthly salary by the employers and

³ Sock-Yong Phang & Wing-Keung Wong (1997) Government Policies and Private Housing Prices in Singapore. Published in *Urban Studies*, Volume 34, Issue 11, November 1997, Pages 1819-1829.

<http://doi.org/10.1080/0042098975268>

⁴ retrieved from: (<http://www.hdb.gov.sg/cs/infoweb/residential/selling-a-flat/eligibility>)

employees.⁵ Therefore, this study attempts to see whether income are moving together with house price in Singapore in the long run.

Literature review

As previously mentioned, there are a number of literatures on the relationship between house price and income. According to Joshua Gallin, (April 2003), many in the housing literature argue that house prices and income are cointegrated. However, he found that cointegration tests have low power for this relationship especially in small samples. Hence, he used panel-data tests to find the cointegration. He cited the work of Meen (2002) and others on how house prices and income are considered to be linked by a stable long-run relationship; they may drift apart temporarily, but they will return to their long-run equilibrium in the long-run.

In this study, all the variables are found to be moving together in the long run and both HDB resale price index and income are the most exogenous in terms of their relative order of exogeneity. In Singapore, this may be true since there is government policy intervention in the HDB flat prices and the resale prices are determined by the market when sold in the open market from previous home owners agreed upon between the two parties. While on the other hand, income seems to be exogenous because it is affected by external causes indirectly since disposable income was used in this study as proxy to income after taxes. Taxes are part of government's fiscal policy hence when we see Singapore's economy, it is heavily reliant on imports.⁶ The policy implication of this is that it is therefore controlled by external factors indirectly.

⁵ Retrieved from: <https://www.economist.com/news/asia/21724856-subsidies-are-irresistible-but-come-social-controls-why-80-singaporeans-live>

⁶ Retrieved from: Donald Low: Fiscal Management in Singapore (shows that HDB resale price index has a significant role to explain the forecast variance for the rest of the variables)

Data Methodology

Sources of Data

This study employs secondary data which are collected from DataStream and some are sourced from (Data.gov.sg). For consistency, the frequency for the variables are all quarterly data taken from the period quarter one year 1990 until quarter four 2017. Most of the literature use and have almost the same proxies such as inflation, demand and supply of the houses, interest rate and income. For this study, GDP (gross domestic product, CPI (Consumer Price Index), and unemployment rate are taken as explanatory variables to explain the house price and income relationship. Unemployment rate is included to see whether it is related to local housing prices. Based on Employment Research by Economic Research Federal Reserve Bank of St. Louis⁷, they found that house prices are negatively correlated with unemployment rate which mean when there is large decrease in housing prices, they will experience larger increase in unemployment rate due to the fact that larger house price declines during downturns will lead to larger declines in local consumption spending which then further depress the local economy.

HDB resale price index tracks the overall price movement of the public residential market.

Model

The HDB resale price index can be modelled as follows:

$$\text{HDBI} = B_0 + B_1\text{DI} + B_2\text{UR} + B_3\text{GDP} + B_4\text{CPI} + e$$

Where HDBI = HDB Resale price Index

DI = Disposable income

UR = Unemployment Rate

GDP = Gross domestic product

CPI = Consumer Price index (Proxy inflation)

⁷ Retrieved from: <https://research.stlouisfed.org/publications/employment-research/is-local-unemployment-related-to-local-housing-prices>

This study employs time-series technique to find the relationship between house price and income in both long run and short run relationship in Singapore.

In the first step, before we can find the cointegration, stationarity test was done on all the variables. Before that, all variables were transformed to logarithm to standardize the variance. Next, we have to test the unit root for all the variables by using the Augmented Dickey fuller (ADF), Phillips Perron (PP) and also KPSS test. In these tests, we have to see whether all the variables are stationary in the order of I(1). This is necessary because, in the step of cointegration test, Johansen’s test requires the variables to be stationary at I(1).

LOG FOR M	VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
	LHDBI	ADF (3) = AIC	216.4793	- 2.8720	- 3.4523	Non-Stationary
		ADF (1) = SBC	209.4150	- 2.7811	- 3.4523	Non-Stationary
	LDI	ADF (5) = AIC	345.7016	- 2.6394	- 3.4523	Non-Stationary
		ADF (5) = SBC	335.0478	- 2.6394	- 3.4523	Non-Stationary
	LUR	ADF (1) = AIC	61.3513	- 2.5430	- 3.4523	Non-Stationary
		ADF (1) = SBC	56.0244	- 2.5430	- 3.4523	Non-Stationary
	LGDP	ADF (4) = AIC	270.9262	- 2.3621	- 3.4523	Non-Stationary
		ADF (1) = SBC	265.1945	- 2.6100	- 3.4523	Non-Stationary
	LCPI	ADF (2)=AIC	397.9051	- 1.7138	- 3.4523	Non-Stationary
		ADF (1) =AIC	392.0533	- 1.4673	- 3.4523	Non-Stationary

1st Diff erence	VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
	DHDBI	ADF (5) = AIC	211.7949	- 4.2784	- 3.4527	Stationary
		ADF (1) = SBC	205.6949	- 5.0871	- 3.4527	Stationary
	DDI	ADF (5) = AIC	340.3512	- 4.2268	- 3.4527	Stationary
		ADF (4) = SBC	330.0787	- 6.0295	- 3.4527	Stationary
	DUR	ADF (3) = AIC	57.7851	- 6.2945	- 3.4527	Stationary
		ADF (1) = SBC	52.4664	- 7.5429	- 3.4527	Stationary
	DGDP	ADF (3) = AIC	265.9323	- 5.8485	- 3.4527	Stationary
		ADF (1) = SBC	258.7391	- 6.6226	- 3.4527	Stationary
	DCPI	ADF (1) = AIC	393.1066	- 4.5426	- 3.4527	Stationary
		ADF (1) = SBC	- 387.7987	- 4.5426	- 3.4527	Stationary

From the results above we can see that all variables are stationary after first difference which allows us to use the basic Johansen cointegration test.

We then can determine the order of VAR by looking at the highest AIC and SBC and check its corresponding results. AIC gives the best maximum likelihood order of lags and less concerned over parameters. While on the other hand, SBC is more concerned on over parameter and chooses the lowest order of lags. The results are as follows,

Order	AIC	p-Value	C.V.
5	1271.1	[.014]	5%
Order	SBC	p-Value	C.V.
1	1205.4	[.014]	5%

Table 1: VAR Order

AIC shows maximum of five lags while SBC shows minimum of 1 lag. AIC predicts the best order of lags, hence maximum lag of five was taken for the cointegration test after testing the autocorrelation diagnostic test. Since, no serial correlations were found in the test.

After determining the number order of lags, we used Engle-Granger and Johansen cointegration test to see whether they have long run relationship among the variables. In this test 1 cointegration was found implying there is long run relationship between the variables. The results are as follows,

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix					
Null	Alternative	Statistic	95% Critical Value	90% Critical Value	Results
R=0	R=1	55.1883	37.86	35.04	1 cointegration
R<=1	R=2	20.9158	31.79	29.13	
Cointegration LR Test Based on Trace of the Stochastic Matrix					
Null	Alternative	Statistic	95% Critical Value	90% Critical Value	Results
R=0	R=1	107.0366	87.17	82.88	1 cointegration
R<=1	R=2	51.8483	63	59.16	

Table 2: Cointegration test

Upon confirming the number of cointegrating vectors from the table above, we then proceeded to LRSM (the long run structural modelling). This was used to find meaningful theoretical relationship among the variables in the long run both exact-identifying and over-identifying.

VRBL	PANEL A	PANEL B	PANEL C	PANEL D	PANEL E	PANEL F
LHDBI	1 (*NONE*)	1 (*NONE*)	1 (*NONE*)	1 (*NONE*)	1 (*NONE*)	1 (*NONE*)
LDI	-19.3032 (-12.2157)	0 (*NONE*)	15806.9 (-97697.8)	-9.3748 (-1.3277)	-8.5618 (-1.8021)	0 (*NONE*)
LUR	-0.025542 (-0.42557)	-0.54853 (-0.2083)	0 (*NONE*)	-0.22473 (-0.16607)	-0.46857 (-0.13511)	0 (*NONE*)
LGDP	5.324 (-5.9671)	-3.4067 (-0.76423)	-7462.8 (-46109.6)	0 (*NONE*)	0.31442 (-1.1066)	0 (*NONE*)
LCPI	9.2461 (-8.5711)	-4.1185 (-1.3108)	-8708.9 (-53827.7)	2.7587 (-1.5352)	0 (*NONE*)	0 (*NONE*)
Trend	0.16113 (-0.067465)	0.052754 (-0.010876)	-94.1833 (-582.4594)	0.11547 (-0.015885)	0.11112 (-0.016077)	-0.0066898 (-0.0033302)
CHSQ(1)		31.3910[.000]	3.5652[.059]	3.9402[.047]	8.5432[.003]	37.0313[.000]
Standard Error in parentheses						
Panel B: Restriction less than 5% - Restriction is wrong i.e. Beta not equal to 0.						
Panel C: Restriction is B=0 **not converged. No results after 11300 iterations						
Panel D: Restriction less than 5% - Beta not zero						
Panel E: Restriction less than 5% - Beta not zero						
Panel F: Restriction is not correct. It means jointly significant.						

Table 3: LRSM

As we can see, in the exact-identification restriction, variable HDB resale price index was normalized equal to one as the main focus variable. The results show that all of the other variables turn out to be insignificant. Hence, to test this whether it is true or not, over-identification was used by putting restrictions on each of the variables to see whether they are still insignificant on its own and also jointly significant after putting restrictions. All variables turned out to be significant, hence the restrictions are not correct which mean the coefficients of each variable is not equal to zero, in other words have some values against the theoretical relationship in the long run. Therefore, it is not appropriate to drop these variables.

Most of the literatures have used VECM (vector error correction) or VDC (variance forecast error decomposition) method to test Granger-causality. VDC is a way of characterizing the dynamic behavior of the model. It breaks down each variable into proportions including its own, thus, able to tell us the relative exogeneity and endogeneity of the variables which VECM lacks. The table below shows the results from VECM model of which only able to tell

us the endogeneity and exogeneity only but not the relative order. The relative endogeneity and exogeneity can be found from VDC results. Only generalized VDC was employed due to its advantages and not bias as compared to the orthogonalized VDC since generalized VDC does not have any restrictive assumptions. Generalized VDC does not depend on the particular ordering of the variables in the VAR.

ecm1(-1)	Coefficient	Standard Error	T-Ratio [Prob.]	C.V.	Result
dLHDBI	-.031967	.011009	-2.9038[.005]	5%	endogenous
dLDI	-.0065511	.0038768	-1.6898[.095]	5%	exogenous
dLUR	-.088682	.043107	-2.0572[.043]	5%	endogenous
dLGDP	-.0096315	.0065333	-1.4742[.144]	5%	exogenous
dLCPI	.7925E-4	.0018851	.042040[.967]	5%	exogenous

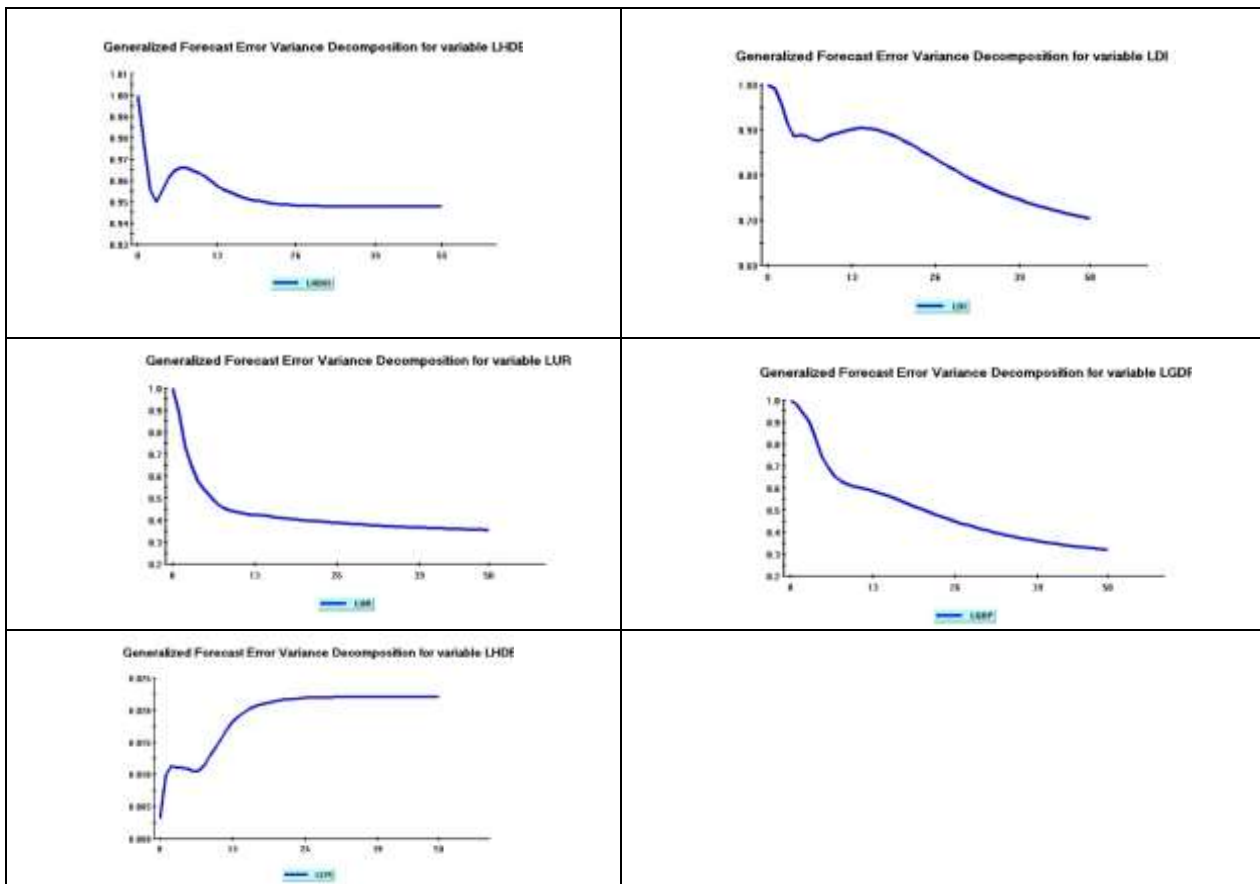
Table 4: VECM results.

Generalized Approach						
Variable	LHDBI	LDI	LUR	LGDP	LCPI	TOTAL
13 weeks LHDBI	95.77%	3.93%	1.63%	3.08%	1.85%	106.27%
LDI	15.54%	90.18%	0.28%	3.65%	2.46%	112.10%
LUR	7.71%	41.65%	42.52%	22.63%	3.62%	118.13%
LGDP	13.51%	13.72%	2.05%	58.79%	15.42%	103.48%
LCPI	17.22%	4.70%	11.54%	34.15%	70.69%	138.29%
Exogeneity	95.77%	90.18%	42.52%	58.79%	70.69%	
Ranking	1	2	5	4	3	

Table 5: VDC Results

Generalised Approach								
Variable	LHDBI	LDI	LUR	LGDP	LCPI	TOTAL	SELF-DEP	RANK
13 weeks LHDBI	90.12%	3.70%	1.53%	2.90%	1.74%	100.00%	90.12%	1
LDI	13.86%	80.45%	0.25%	3.25%	2.19%	100.00%	80.45%	2
LUR	6.52%	35.26%	35.99%	19.16%	3.06%	100.00%	35.99%	5
LGDP	13.05%	13.26%	1.98%	56.81%	14.90%	100.00%	56.81%	3
LCPI	12.45%	3.40%	8.34%	24.69%	51.11%	100.00%	51.11%	4
Exogeneity	90.12%	80.45%	35.99%	56.81%	51.11%	100.00%		
Ranking	1	2	5	4	3			
			LUR	<LCPI	<LGDP	<LDI	<LHDBI	

Table 6: VDC after normalizing the data.



After normalizing the variance forecast decomposition generalized approach. Based on the results shown above when comparing VECM and VDC, VECM and VDC results contradicts each other. The VECM results shows, HDB resale price index variable as an endogenous variable. However, in VDC show, HDB resale price index is the most exogenous variable. This difference could be due to the fact that, VDC is a forecast based on the past results. The implication is that, house prices are rising. The upward price movements are expected. Hence, it is realistic to expect the house prices are moving upward, and policymakers should consider to address this problem.

At the end of forecast horizon number 13, forecast error variance of HDBI variable explained by its shock of 90.12%, Disposable income at 80.45%, Unemployment rate explained by 35.99%, GDP at 56.81% and lastly CPI at 51.11%. This result shows that HDB resale price index has a significant role to explain the forecast variance for the rest of the variables.

Then in Impulse Response Function (IRFS) which works the same as VDC, the only difference is, it is being represented by graph. And finally, we are at Persistence Profile to

test how long the whole system to stabilize after the variables are shocked by external factors for example, the global crisis.

In addition to these tests, ARDL also was used to test the cointegration to address the limitation of Johansen's test. In ARDL it does not have any restrictive assumption as the Johansen's cointegration test which needs the variables to be stationary at I(1) after first difference. ARDL does not assume this and able to capture whether variables are both stationary at I(0) or at I(1).

In ARDL, after addressing the stationary tests we then find the cointegrating vectors by computing the F-statistics of each different dependent variables and comparing it with F-table of Pesaran. If it is lesser than the lower bound, then we cannot reject the null of no long run relationship among the variables. If it is greater than the upper bound, then we can safely reject the null of no cointegration or co-movement among the variables in the long run. However, if the value falls in between then the result is therefore inconclusive. In this study, only one cointegrating vector was found for the dependent variable of LHDBI which is shown below:

Max Lag:	Significance Level	Cointegration	Dependent Var	F-Statistics
4	5%	No	LHDBI	F(5,81)= 1.9862[.089]
4	5%	Yes	LDI	F(5,81)= 7.8225[.000]
4	5%	No	LUR	F(5,81)= 2.5026[.037]
4	5%	No	LGDP	F(5,81)= 1.2369[.300]
4	5%	No	LCPI	F(5,81)= 2.1396[.069]

Conclusion

Housing affordability and increasing house prices have been an issue for any local economy due to its nature relating to the economy of the country. Given that Singapore is unique and has limited land spaces, majority of its people choose HDB flats for its affordability.

This study employed time series techniques by testing for cointegration, LRSM (long run structural modelling), VECM (vector error correction model), VDC (variance decomposition), IRF (impulse response function) and PP (persistence profile). Furthermore, macroeconomic factors were also factored in this study. In the long run, all variables have theoretical relationship among each other on HDB resale price index. However, the speed of adjustment is relatively slow when coming back to equilibrium.

HDB flats prices are relatively controlled by HDB (housing development board) of Singapore. Although, the VDC and VECM results contradict each other, it shows that HDB resale price index has a significant role to explain the forecast variance for the rest of the variables. And it is inconclusive as to whether income or house price lead or lag, however in this study, the most exogenous variable is house price which is determined by market forces based on resale price index, while income is related to the local economy. And surprisingly, unemployment rate is the most endogenous which means it is following the other macroeconomic variables as well as income and house prices in Singapore. This is particularly true because when the Singapore's labour market improved, it means that the economic activity is doing well hence, low unemployment rate and vice versa. Given that our model is made up of most of the macroeconomic variables, it is not surprising to see this result.

In my humble opinion, the policymakers can only control the unemployment rate by stabilizing the economy through its fiscal policy which in Singapore is characterized by strong emphasis on medium and long-term objectives. The limitation of this study would be that, lending rate was dropped in the beginning of the study which might have some theoretical explanation in addition to these variables, hence future research could add more variables and not limiting to few variables to see the long run relationship among these variables.

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