Estimating bubbles and affordable housing price trends: A study based on Singapore

by

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Abstract

Policy makers often impose some cooling measures on the housing market when housing prices rise fast. Such policies yield limited success if housing prices are driven up by fundamentals. A fundamental price trend may not necessarily be an affordable one. Unaffordable housing price trends increase the mortgage burden of households. Estimating these different price trends provides valuable information to policy makers. This paper presents an empirical methodology to separate out a housing price trend into fundamental and affordable components. The gap between actual and fundamental trend is attributed to expectations driven persistence of housing price inflation. This is the component that cooling measures are usually aimed at. Affordable housing price trend is defined in terms of a measure of lifetime income. Affordability requires the house price to lifetime income ratio to be stationary with a certain mean. Fundamentals need to be adjusted to obtain this outcome. Analyzing Singapore data using this methodology reveals some interesting observations.

Key Words: Fundamental housing price, affordable housing price, lifetime income, counter-factual simulations

JEL Classification: R21, D31.

* Corresponding author, Tilak Abeysinghe
1. Introduction

Although house prices are well known to form bubbles, separating the bubble and non-bubble components is a challenging task because of the difficulty of working out a reference price level that represents the unobserved non-bubble component. There are various definitions of asset price bubbles but from an operational point of view we align with those who define bubbles in relation to some fundamental variables (see Siegel, 2003 for some references). By this definition the fundamentals determine the non-bubble component of the price level. One question is how to estimate this fundamental price level. A price level determined by the fundamentals, however, may not necessarily be an affordable price level. For example, population pressures tend to drive city house prices well above affordable levels. Another important question, therefore, is how to determine an affordable housing price level. The objective of this exercise is to develop an empirical methodology to answer these two questions and analyze housing price data from Singapore.

Singapore is an interesting case study in this regard. The country has a small private housing sector and a large public housing sector with private ownership. Singapore has one of the highest home ownership rates (about 90%) in the world. Singapore government desires to see house prices appreciate over time at an affordable rate. Through home ownership the government is trying to achieve a social objective of “heartland-feeling” in this global city. Despite regular interventions by the government, the Singapore housing market has gone through a number of price cycles with prices escalating way beyond any expectation. Persistent unaffordable increase in housing prices may bring about unexpected negative consequences. For example, Abeysinghe and Choy (2007) observed that in Singapore increasing housing wealth as a result of increasing housing prices does not create a positive impact on consumption expenditures because of a lack of monetizing opportunities of housing wealth. They

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1 See Gu (2008) and Lum (2011) for a review of Singapore government policies in the housing market.
observed, however, that increasing housing prices render a substantial negative effect on consumption expenditures leading to a substantial secular drop in average propensity to consume (APC). This has exposed the economy more to volatile external forces. Yi and Zhang (2010) observed that rising housing prices in Hong Kong as a major cause for the precipitous decline of the state’s total fertility rate (TFR). Abeysinghe (2011) noted similar results for Singapore. The negative impact of rising housing prices may not be limited to these areas. When house prices appreciate it is not clear exactly what drives the appreciation, fundamentals or something else. In this respect the results of this paper provide important guidelines to the policy makers.

There is a sizable literature on modeling residential property prices. Under the so-called first generation models pioneered by Muth (1960) followed by others like Smith (1969) stock and flow demand for housing was modeled under the assumption of a highly elastic housing supply. Obviously these models underwent the scrutiny of others for many shortcomings. This gave rise to further improvements under the next generation models that used either the stock-flow framework or the asset pricing approach. This led to incorporating more comprehensive measures of user cost of housing, supply side features, disequilibrium, demand side expectations, supply side expectations, house vacancy rate specifications, and land supply issues.\textsuperscript{2} We incorporate some key features of this literature to our modeling strategy but depart from the literature in the way we address the two main questions raised earlier.

The methodology of estimating the fundamental housing price trend is discussed in Section 2.1. Since buying a house is a long term commitment, housing affordability has to be measured in relation a measure of permanent income. The income measure we propose is lifetime income and the methodology of obtaining estimates of lifetime income for different income deciles is presented in

Section 2.2. We propose to measure housing affordability in relation to the growth rate of lifetime income. Section 3 provides a description of computational methods of the variables used in our regressions. Readers may skim through this section to pick up the variable notations and move on to the empirical results of sections 4 and 5 directly. Section 6 provides a summary of the methodology and the key findings from the analysis of the Singapore housing prices.

2. Methodology

2.1 Estimating the fundamental housing price level

There are three price levels that we need to consider, equilibrium housing price, fundamental housing price and affordable housing price. Equilibrium housing price is usually expressed through a present value relationship that is often used to model house price-to-rent ratio (Meese and Wallace, 1994; Schreyer, 2009; Igan and Loungani, 2012). Holly et al. (2010) converted this relationship to a house price-to-income ratio. This transformation requires the price-income ratio to be stationary. As we shall see later, the price-income ratio is unlikely to be stationary in situations where housing affordability has been deteriorating. To remove this non-stationarity we have to introduce other fundamental variables into the model.

In a simple one period setting the equilibrium housing price is obtained by equating the expected rate of return from home ownership to the rate of homeowner cost of capital (Meese and Wallace, 1994). In order to model log-transformed variables it would be easier to work with the log-linear present value formulation that Campbell and Shiller (1988) introduced for financial assets.\(^3\) To stick to the same symbols let \( p_i = \ln P_i \) be the log of house price and \( d_i = \ln D_i \) be the implicit rental (dividend) for

\(^3\) See Cochrane (2005) for a textbook treatment and Campbell (2008) and Engsted et al. (2012) for further assessments of the transformation.
When the price-rent ratio is stationary the Campbell-Shiller approximation to 
\[
\log \text{ return } = \ln\left(\frac{(P_{t+1} + D_{t+1})}{P_t}\right) \approx k + \rho p_{t+1} + (1 - \rho)d_{t+1} - p_t = 
\]
\[k - (p_t - d_t) + \Delta d_{t+1} + \rho(p_{t+1} - d_{t+1}), \text{ where } \rho = 1/(1 + P/D) \text{ and } k \text{ is a constant. Here } P/D \text{ is the steady state level of the price-rent ratio. In equilibrium the rate of return is equal to the rate of homeowner cost of capital. Therefore, writing the above equation for } p_t - d_t, \text{ solving forward and taking expectation leads to the present value formulation:}
\]
\[
p_t - d_t = k / (1 - \rho) + E_t \left[ \sum_{j=1}^{\infty} \rho^{j-1} (\Delta d_{t+j} - r_{t+j}) \right]
\]
where \( E_t \) indicates expectation conditional on information at \( t \). This fundamental bubble-free formulation shows that the price-rent ratio, apart from the constant term, is the discounted present value of the expected rent growth rate adjusted for the homeowner cost of capital.

In general, \( p_t \) and \( d_t \) are \( I(1) \) variables and the formulation in (1) requires \( p_t - d_t \) to be \( I(0) \). Although the price-income ratio is our primary focus as in Holly et al. (2010), it may not be an \( I(0) \) variable as in the case of Singapore. We can, however, replace \( d_t \) with \( \beta'x_t \), where \( x_t \) is a vector of fundamental variables, including income, such that \( p_t - \beta'x_t \) is \( I(0) \). The expectation term in (1) involves \( I(0) \) variables which are not observed. Both rational expectations (Hansen and Sargent, 1980) and extrapolative expectations (Lansing, 2006, 2010; Granziera and Kozicki, 2012) show that the expected term in (1) can be replaced with relevant observed \( I(0) \) variables. Therefore, we can formulate a more general econometric model within the cointegrating and error correction model (ECM) framework.

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4 Usually these variables are expressed in real terms. The inflation effect, however, cancels out in the formulation in (1). Apart from this, we prefer modeling in nominal terms because the consumer price index (CPI) tends to increase when house prices increase and the real house price (P/CPI) tends to be over deflated especially during housing price bubbles.
Our first question is how to estimate the long run price level based on its fundamental determinants. Let \( p_t^* = \beta_0 + \beta'x_t \) be the long run (log) price determined by a \( k \times 1 \) vector \( x_t \) of the fundamental variables. As mentioned above, we require

\[
p_t = \beta_0 + \beta'x_t + u_t
\]

(2)

to be a cointegrating relationship such that \( u_t \sim I(0) \). Although we can obtain the estimates of the parameters in (2) either using OLS or some other method, the predicted price \( \hat{p}_t = \hat{\beta}_0 + \hat{\beta}'x_t \) is not the \( p_t^* \) that we are looking for. Since these parameter estimates are obtained such that \( \sum \hat{u}_t = 0 \) the predicted price line will pass through the center of \( p_t \) line. When price bubbles are present the \( \hat{p}_t \) line will invariably lie above the \( p_t^* \) line.\(^5\) This does not help us in gauging the price gap \( (p_t - p_t^*) \) that would be of policy interest.

One way to estimate \( p_t^* \) is to specify an ECM of the form

\[
\Delta p_t = \phi_0 + \sum_{i=1}^{p} \phi_i \Delta p_{t-i} + \gamma'z_t + \sum_{j=1}^{m} \sum_{i=0}^{p} \delta_{ji} \Delta x_{j,t-i} + \alpha[p_{t-1} - \beta'x_{t-1}] + \varepsilon_t
\]

(3)

where \( z_t \) is a vector of short-run determinants of house price inflation such as the indicators of speculative activities in the housing market. The lagged dependent variables, \( \Delta p_{t-j} \), capture the short run persistence of housing price inflation. Such persistence may result from price expectations. When house prices are rising fast the buyers may rush to buy a house because of the fear of further increase in price, which will drive prices further up. When house prices are falling buyers may delay the purchase of a house with the hope that the prices may fall further, which will accentuate the price fall. Such

\(^5\) The opposite will happen if negative bubbles (troughs) are dominant.
persistence may cause short run deviations of housing price from the fundamental price or may even lead to the formation of price bubbles through the interaction of other factors (Glaeser et al., 2008).

If (3) is well specified, a dynamic simulation using the full model in (3) will track the actual $p_t$ very closely. If we set $\phi_1 = \gamma = 0$ what is left in (3) are the fundamental determinants of the house price inflation. We can therefore obtain $p_t^*$ as

$$p_t^* = \phi_0 + (1 + \alpha)p_{t-1}^* + \sum_{j=1}^{m_1} \sum_{i=0}^{m_2} \delta_{ji}\Delta x_{ji} - \alpha \beta'x_{i-1}. \tag{4}$$

Given $-1 \leq \alpha < 0$, a dynamic simulation using (4) will yield a long run price that will converge to the same price $p_t^*$ regardless of the starting point $p_0^*$. The trend of the price line is determined by that of $\beta'x_i$.

While $p_t^*$ is determined by fundamental demand-supply forces there could be another price level $p_t^{**}$ that could be deemed desirable in terms of sustaining housing affordability. When demand pressure outstrips the supply, $p_t^*$ will rise faster than $p_t^{**}$. Obviously a persistent positive gap of $(p_t - p_t^*)$ or $(p_t - p_t^{**})$ indicates a buildup of household mortgage debt. We can define $p_t^{**}$ as the price level that renders $\ln(P_t/Y_t)$ stationary. Here $Y_t$ is a measure of household income. In other words, $\ln P_t$ should share the same trend as that of $\ln Y_t$. In this context what measure of $Y_t$ that we should consider becomes important.
2.2 Estimating lifetime income (W) for assessing housing affordability

A convenient choice for income is per capita disposable income (Yd). One problem of using this in the assessment of housing affordability is that Yd is a measure of average income. As income inequality increases the average income biases towards higher income groups. A more robust choice would be the median income, or some quantile measures of income. Another problem of using Yd is that \( P_t / Yd \) does not correspond to the often used mortgage payment to income ratio for affordability assessment. Both these measures focus on short run affordability. For this reason Abeysinghe and Gu (2011) have proposed a lifetime income measure \( W \) and used the ratio \( P_t / W \) to assess housing affordability. This ratio under some conditions is the same as the standard measure of mortgage payment to income ratio; but it has some advantages over the latter. Typically a price-income ratio less than 30% is taken to mean affordable housing prices.

Lifetime income is the discounted present value of the future income stream of a household or an individual. For this we require the age-income profile of a household or an individual. When income data by age and year are available it is possible to trace the income of the same birth cohort as they age. However, given the limited data available, complete age-income profiles can be constructed only for a few cohorts. Incomplete age-income profiles have to be filled using predicted values from a regression. The regression that Abeysinghe and Gu (2011) adapted from Moffitt (1984)) to estimate the age-income profile of a representative household in a birth cohort can be written as:

\[
y_i = \alpha_0 + \alpha_1 \text{Age}_i + \alpha_2 \text{Age}^2_i + \sum_{k=2}^{T-1} \gamma_k C_k + \epsilon_i
\]  

If income \( y \) is lognormally distributed or log of income is normally distributed with mean \( \mu \) and variance \( \sigma^2 \), then \( E(y) = e^{\mu + 0.5\sigma^2} \) and \( \text{Median}(y) = e^{\mu} \). This gives, \( E(y) / \text{Md}(y) = e^{0.5\sigma^2} \) and as the variance of log-income distribution increases the mean departs from the median at the rate given above.
where \(i=1,2,...,A\) is the \(i\)th age representing year in index form, \(t=1,2,...,T\) is the \(t\)th year index, \(k=A-i+t\) is the \(k\)th cohort index, \(C_k\)'s are cohort dummies and \(y_{it}\) is the log of average household income. Note that the income data for (5) are arranged in a panel format, for each age \(i, t=1,2,...,T\). The quadratic age term captures the usually observed hump-shaped age-income profile of a household. The cohort dummies allow for shifts in the age-income profile from one birth cohort to another.

If income by household is available annually then the quantile regression technique proposed by Koenker and Bassett (1978) can be used to obtain quantile coefficient estimates of (5) and then derive the quantile age-income profiles. The income data available to us are in deciles (see Section 3) and we cannot use the quantile regression techniques directly. However, Chamberlain (1994) has shown that when the right hand variables of the regression are discrete (as in the case of our regression 5) the least-square method on group-specific quantile summary statistics provides consistent estimators for the regression quantile coefficients and they are asymptotically normally distributed under mild regularity conditions (see Bassett et al., 2003 and Chetverikov et al., 2013 for further developments and applications). We can, therefore, estimate (5) or its variants discussed below by OLS for different income deciles to obtain the quantile age-income profiles.

Usually income data are available by age groups, say \(L\) years (usually \(L=5\)). To correspond to this we have to convert years also into \(L\) year groups. If \(A\) and \(T\) are taken to be multiples of \(L\), then there is a total of \((A/L)(T/L)\) observations to estimate (5) with \((A+T)/L-1\) cohort dummies. This grouping provides age-income profiles of different birth cohorts also at \(L\)-year intervals. Abeysinghe and Gu (2011) followed this estimation method and used the spline interpolation method in SAS to obtain an annual series of lifetime income values.

An alternative method is not to group years into five-year intervals, but to introduce enough cohort dummies to estimate the age-income profile at yearly intervals. Under this setting there are \((A/L)T\)
observations to estimate (5) with $A+T-L$ cohort dummies. One disadvantage of the alternative method is that the number of observations available for estimating the cohort coefficients of the older and younger cohorts drops substantially leading to more volatile cohort coefficient estimates. Since we expect the lifetime income to move smoothly among the consecutive cohorts we suggest applying a smoothing filter to the annual cohort coefficients. In this exercise we use a spline smoothing method. Fig. 1 shows the annual cohort coefficient estimates from our alternative methodology and their smoothed values for the median income group.

![Graph](image)

**Fig. 1.** Cohort coefficient estimates solid line and their smooth values dashed line for the median income group
3. Data and computation methods of variables

*Residential property price (P)*

Singapore’s residential property market has three major segments, private housing, new public housing and resale public housing. Private housing caters mainly to high income groups. Public housing in Singapore is provided by the Housing and Development Board (HDB) and is also known as HDB housing. New HDB houses are sold to Singapore citizens at a highly subsidized rate. After five years of owner occupation these properties can be sold in the open market. This is known as the HDB resale market. Price data of new HDB properties are not available. Therefore, we study only the private and HDB resale housing prices. Even for these markets sufficiently long time series are available only for median housing prices. The Urban Redevelopment Authority has published a quarterly private housing price index since 1975 and the HDB has published a quarterly HDB resale price index since 1990. We converted these indices to price levels using median price levels of 2005. Fig. 2 presents the private and HDB median housing prices. The large price gap between the two markets and upward trend of prices with common cycles are some observations to be noted down.

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7 Unless otherwise specified the main source of data used in the study is the STS database of the Department of Statistics, Government of Singapore.
Fig. 2. Private and HDB median housing prices (Singapore $)

Housing stock (HS)

Because of data limitations on the number of housing units available, we constructed quarterly housing stock series from constant dollar investment in private and public housing markets using the perpetual inventory method. This investment-based housing stock accounts for quality variation in units and also contains supply-side expectations. We lagged the HDB series by five years because the new HDB units can be sold only after five years of owner occupation.

Population (POP)

Population data are available on an annual basis. Singapore’s resident population consists of Singapore citizens and permanent residents. This component changes slowly and smoothly. We therefore, used the spline interpolation method in SAS to obtain the quarterly resident population. The most volatile component of the population is non-permanent residents. A large proportion of this population is foreign workers. We used the labor force data that are available quarterly to construct a
quarterly series of working age foreign worker population. The total population is the sum of these two components. In the private housing price equation we used the total population. In the HDB price equation we used the resident population because HDB houses can be bought only by Singapore residents.

*Lifetime income (W)*

We obtained average household nominal income by age and year by income deciles from the Department of Statistics, Government of Singapore. Age is for the household head and is grouped into five-year intervals. Annual data are available from 1990. Data from 2000 onwards are available with and without employer’s Central Provident Fund (CPF) contributions. The ratio of income with CPF to income without CPF is about 1.1. We multiplied the data prior to 2000 by 1.1 to adjust them to match the income data with employer’s CPF contributions. We then used the alternative methods described in Section 2.2 to construct age-income profiles by birth cohort for each income decile. We then obtained the discounted present value of household income over age 30-64 using the discount rate of 5% and constructed the lifetime income series by birth cohort; birth year plus 30 becomes the reference year. As in Abeysinghe and Gu (2011) we use age 30 as the age at which a young couple looks for a residential property unit. We denote the lifetime income series thus constructed by \( W_1, W_2 \ldots, W_9 \) to refer to the defiles 1 to 9. To convert these annual series to quarterly we used the spline interpolation available in the SAS software package. Fig. 3 presents these lifetime income series and it highlights the widening income gap between the lower and higher income groups that is of interest for a separate study.  

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8 Note that the series presented in Figure 4 of Abeysinghe and Gu (2011) are in real terms whereas those in Fig. 3 in this paper are in nominal terms. Moreover, the income series of this study includes employer’s CPF contributions that were not available to Abeysinghe and Gu (2011).
Fig. 3. Estimated nominal lifetime income (Singapore $mn) of 30-year old cohorts by income deciles

Savings

By age 30 households have some savings that need to be added to the discounted present value of the future income stream to obtain the complete lifetime income of a household. Constructing meaningful savings series by income deciles from quinquennial household expenditure surveys is not easy. We, therefore, use quarterly per capita CPF balances (overall) in nominal terms to represent accumulated savings.

Disposable income (Yd) and Deposits (Depst)

Lifetime income is a slowly changing quantity (Fig. 3). Therefore, to capture short run effects of income changes we use per capita nominal disposable income and residents’ deposits. Disposable income is calculated as in Abeysinghe and Choy (2007): GDP - taxes - government fees & charges - net CPF contributions. About 60% of the financial wealth of Singaporean households is made up of CPF balances
and residents’ deposits. Our empirical analysis shows that between the two the CPF balances is the key long run determinant of housing prices but deposits may have some short run effects.

*User cost of housing (UC)*

In empirical exercises the user cost of owner occupied housing (the rate of homeowner cost of capital) is often defined as

\[
UC = [(1 - \tau_m)(i + \tau_p) + \delta - \pi]
\]  

(6)

where \(\tau_m\) is the marginal income tax rate, \(\tau_p\) is the property tax rate, \(i\) is the nominal mortgage interest rate, \(\delta\) is the depreciation rate which may be broadly defined to include other maintenance costs, and \(\pi\) is expected capital gains (DePasquale and Wheaton, 1994; Igan and Loungani, 2012). The marginal income tax rate is included in the equation because property taxes and mortgage payments are tax deductible.

Constructing the user cost of housing is problematic because of the difficulty of measuring expected housing price appreciation \(\pi\). Since house prices are subject to bubbles, the use of some averages or projections based on observed housing price to represent expectations in the UC formula tend to produce highly volatile UC series with implausible negative values (Schreyer, 2009). Researchers on this problem have found that the trend movements of the consumer price index (CPI) as providing a much better measure of long term house price expectations (Poterba, 1992; Schreyer 2009). In our exercise we also use the trend movements of the CPI inflation rate to measure the baseline house price expectations. After some experimentation, the baseline CPI inflation rate was obtained by simple exponential smoothing with \(\alpha =0.2\).
The marginal income tax rate in the UC formula was calculated as the income-share weighted average of the marginal tax rates. Let \( \tau_i \) be the marginal income rate for the \( i \)th income bracket \( i=1,2,\ldots,k \), \( Y_i \) be the assessed income of the \( i \)th income group, and \( w_i \) be the income share of the \( i \)th group. Then the average of the marginal income tax rates, \( \tau_m \), can be written as:

\[
\tau_m = \frac{\sum_{i=1}^{k} w_i \tau_i}{\sum_{i=1}^{k} Y_i} = \frac{\text{Total tax assessed}}{\text{Total assessed income}}
\]

where \( w_i = \frac{Y_i}{\sum_{i=1}^{k} Y_i} \). Total tax assessed and total assessed income are available in the Yearbook of Statistics.

As for the mortgage interest rate \( i \) we use the average housing loan rate compiled by the Department of Statistics. This is available since 1983. For the period before 1983 we use the prime lending rate. For HDB housing we take the weighted average of the housing loan rate and HDB concessionary home loan rate with a weight of 0.75 for the former. We set the annual value of \( \delta \) to 0.03. The UC series can be computed from 1976Q1 and shows a downward trend; it dropped from more than 14% in 1986 to below 1% by the end of 2012.

*Sub-sale Rate and Foreign Ownership Rate*

An important indicator of speculative activities in the private housing market in Singapore is the sub-sale rate. This measures how frequently a new residential unit under construction is sold before its completion. This data series is available only from 1995Q1. Another variable that is alleged to cause large price upswings is the inflow of foreign capital to the private housing market (Lum, 2011; Liao et al. 2012). Time series data on capital inflow is not available. As a proxy we use the proportion of uncompleted private residential units purchased by foreigners. These data are available only from
4. Fundamental housing price trends and bubbles

To estimate long run housing price trends determined by the fundamentals we first formulate the cointegrating regression (2) as:

$$\ln(\frac{P_t}{W_t}) = \beta_0 + \beta_1 \ln(\frac{HS_t}{POP_t}) + \beta_2 \ln CPF_t + \beta_3 UC_t + \beta_4 UC.Dum08 + u_t$$  \hspace{1cm} (7)

The variables in (7) were defined in the previous section (see also notes to Table 1). Following DePasquale and Wheaton (1994) $HS/POP$ represents a given stock of housing supply per capita. As mentioned in the previous section our investment-based housing stock measure contains supply side expectations. The other variables represent demand side fundamentals. Unit root tests indicate that the variables in (7) can be assumed to be unit root processes. Dum08 in (7) is a step dummy that takes value 1 from 2008Q1. The recursive OLS estimates of $\beta_3$ become less stable after 2007 because of a sharp drop in the $UC$ variable. With the interaction variable, $UC.Dum08$, the recursive estimates of all the coefficients of (7) become highly stable.\(^{10}\)

Since we have only the median house prices we wanted to assess which lifetime income variables to be used in the regression. We first carried out a residual based ADF test for cointegration over the sample period 1976-2007 without the dummy. Since private housing in Singapore is for high income groups we used the income variables from $W5$ to $W9$ in (7) for this test. We find that cointegration cannot be rejected at the 10% level only for the high income groups $W8$ and $W9$. As for HDB housing we carried out this test for income groups $W1-W6$. The residual based ADF test does not support

\(^9\) Unrestricted estimates show that the coefficient of $\ln W_t$ can be restricted to unity.

\(^{10}\) Trying to obtain the cointegrating vector in (7) through dynamic models (Bardsen, 1989; Stock 1993; Johansen, 1995) proved unsatisfactory because of the distortionary effects of price bubbles on the estimates.
cointegration for HDB housing prices. This could be due to the shorter sample period 1990-2007. Nevertheless we estimated the full regressions and carried out simulations using W8 for private housing and W5 for HDB housing.

The estimation results are reported in Table 1. The coefficient estimates in Panel 1 have the expected signs and their recursive estimates are highly stable. Although the t-statistics of these cointegrating regressions may not follow the normal distribution they, except for that of UC, are substantially larger than the standard critical values. Recursive estimates of the ECMs in columns (1) and (3) in Panel 2 are also stable and meaningful although some residual diagnostics fail. We retained only the statistically significant estimates in these regressions. Although the ADF test rejects cointegration for HDB housing price, the adjustment coefficient of the EC term indicates that it is a cointegrating relationship though the t-statistic is not as large as that for the private housing price.\textsuperscript{11} Column (2) in the table was considered to examine the effect of two additional variables (see below). Despite the reduced sample size the estimates in column (2) are not very different from those in column (1).

\textsuperscript{11} Residual based ADF test for cointegration is well known to have low power.
Table 1. Regression estimates for private and HDB housing prices

<table>
<thead>
<tr>
<th>Panel 1: Cointegrating regression</th>
<th>Private</th>
<th>HDB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dept variable</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>( \text{ln}(P_i / W8_i) )</td>
<td>Coeff</td>
<td>t-stat</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.26</td>
<td>-0.67</td>
</tr>
<tr>
<td>( \text{ln}(HS_i / POP_i) )</td>
<td>-1.58</td>
<td>-14.6</td>
</tr>
<tr>
<td>( \text{ln}CPF_i )</td>
<td>1.45</td>
<td>17.5</td>
</tr>
<tr>
<td>( UC_i )</td>
<td>-0.02</td>
<td>-1.88</td>
</tr>
<tr>
<td>( UC.Dum08_i )</td>
<td>-0.10</td>
<td>-6.41</td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.82</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel 2: Error correction model</th>
<th>Private</th>
<th>HDB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dept variable</td>
<td>( \Delta \text{ln} P_i )</td>
<td>( \Delta \text{ln} P_i )</td>
</tr>
<tr>
<td>( \Delta \text{ln} P_{i-1} )</td>
<td>Coeff</td>
<td>t-stat</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.02</td>
<td>-2.93</td>
</tr>
<tr>
<td>( \Delta \text{ln} \text{POP}_i )</td>
<td>0.64</td>
<td>11.1</td>
</tr>
<tr>
<td>( \Delta \text{ln Depst}_{i-1} )</td>
<td>0.43</td>
<td>3.51</td>
</tr>
<tr>
<td>( \Delta \text{ln} \text{Yd}_i )</td>
<td>0.19</td>
<td>1.99</td>
</tr>
<tr>
<td>( \Delta \text{ln} \text{Yd}_{i-1} )</td>
<td>0.22</td>
<td>2.26</td>
</tr>
<tr>
<td>( \Delta \text{SubsaleRate}_i )</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( \Delta \text{ForeignOwnershipRate}_{i-1} )</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.63</td>
<td></td>
</tr>
</tbody>
</table>

Residual diagnostics test p-value Test p-value test p-value
AR 1.64 0.1537 1.59 0.1927 1.50 0.2003
ARCH 2.72 0.0325 0.89 0.4756 0.24 0.9174
Normality 21.50 0.0000 40.37 0.0000 44.06 0.0000
Hetero 1.53 0.1212 0.96 0.5195 1.02 0.4351
Hetero-X 1.87 0.0130 - - 0.99 0.4914
RESET 0.68 0.4124 0.54 0.4673 0.08 0.7767
Sample period 1976Q1 - 2011Q4 1996Q2 - 2011Q4 1990Q1 - 2011Q4

Note: P=median housing price, W5=household lifetime income of 5\(^{th}\) income decile, W8=household lifetime income of 8\(^{th}\) income decile, CPF=per capita Central Provident Fund balances, HS=housing stock, POP=population, UC=user cost of housing, Depst=per capita residents’ deposits, Yd=per capita disposable income, EC=error correction term OLS residuals from the cointegrating regression. Residual diagnostics are those readily available in PcGive.
It is worth highlighting some observations that emerge from Table 1. First, for HDB housing the coefficient of per capita housing stock is much larger in absolute value than that for private housing. Although this was not expected apriori, this seems to capture the fact that HDB caters to more than 80% of the Singaporean households. Therefore, one percent increase in per capita housing stock is likely to have a much bigger effect on HDB housing prices compared to private housing. Second, short run effects of housing stock growth and population growth seem to manifest differently in private and HDB markets (Panel 2). It appears that short run fluctuations in population affect private housing price inflation and not HDB. This is understandable because HDB units cannot be bought by foreigners and they are also subject to renting restrictions. On the other hand, an increase in the HDB housing stock lowers the HDB housing price inflation both in the short run and long run. Third, the effects of the sub-sale rate and foreign ownership rate are not statistically significant. This is partly due to the reduced sample size. The sub-sale rate picks up the speculative activities in the housing market. It dropped sharply after government interventions in the housing market in 1996. Since then speculation in the housing market has remained subdued and the insignificant effect for the sub-sale rate seems to reflect this. Foreign ownership rate, on the other hand, does not seem to be picking up the full impact of foreign capital inflow to the private housing market. To stimulate the housing market out of its slumber during the mid 2000s the government relaxed the rules of foreign ownership of residential properties in Singapore. This led to a substantial pick up in housing prices subsequently and the government had to tighten the rules again (Lum, 2011; Liao et al. 2012). Our proxy variable does not pick up this effect well.

Fig. 4 shows the actual median private housing price and the fundamental price trend simulated from regression (1) in Table 1 based on the formulation in (4) using starting values from 1977Q1 and Q2. Fig. 4 also shows a simulated (dotted) line with starting values from 1995Q1 and Q2 to highlight that it converges to the same trend line regardless of the starting values. Fig. 5 shows the simulated trend line
for HDB median housing price. Housing price bubbles are clearly visible from these figures, one in the early 1980s and the other in the mid 1990s. Government interventions pricked the bubble of the 1990s that resulted in a decade long downward price adjustment before prices started to climb up again above the trend line since 2007. Between 2007 and 2011 both private and HDB housing prices increased by about 12% per year whereas fundamental trend price increase should have been about 7% for private housing and 10% for HDB housing. It seems that the HDB housing price inflation is mostly fundamental driven. Fig. 5 also shows price trend line generated by plugging in W6 to the regression (3) in Table 1. Although we need HDB prices for the 6th decile for a proper study, Fig. 5 shows that recently HDB prices have moved closer to the price generated for the 6th income decile than to the median trend. This brings us to the next question whether the fundamental trend price increases are affordable.

![Graph](image-url)

Fig. 4. Median private housing price P (in log, solid line) and simulated fundamental price trend (dashed line W8). Dotted line uses starting value from 1995Q1 and Q2.
5. Long run housing affordability

The price-to-lifetime income ratio $P/W$ is our housing affordability measure. We simply refer to this as the price-income ratio. Since we have only the median price of private and HDB housing we examine long run housing affordability by the price-income ratio $(P/W_k)_{100}$, $k = 1, 2, \ldots, 9$, where $k$ refers to the $k$th decile or the corresponding percentile. An increase of $P/W$ indicates deteriorating affordability.

As we stated earlier, private housing in Singapore is affordable only by the rich. Therefore, Fig. 6 presents the price-income ratio for median and higher income groups, $P/W5-P/W9$. Since HDB housing is meant for low income groups, Fig. 7 presents $P/W1-P/W5$. The horizontal line in these graphs at 30% indicates the rule-of-thumb value below which housing is assumed to be affordable. These figures reveal a number of interesting observations. First, housing affordability in general shows a deteriorating trend across all income groups. Second, although housing prices have escalated recently to levels above the
1996 peak (Fig. 2), in terms of affordability, the price-income ratios have not deteriorated to the level of 1996. For the median income group $P/W5$ for private housing in 1996 was 93.1% and in 2011 it improved to 52.9%. For HDB units these numbers were 25.8% and 18.3% respectively. In other words, 1996 has been the worst year in terms of housing affordability. Third, recent trends show that median priced private units are only affordable by the top 20% income groups and median priced HDB units are not affordable by the low 20%.

![Fig. 6. Housing affordability for private housing, $P/W$ for median and higher income deciles](image-url)
Since 2007 the price-income ratios have trended upward. We noted in the previous section that the median housing prices have increased by about 12% per year between 2007 and 2011 and the fundamental trend price increase should have been about 7-10%. The average annual growth of median lifetime income has been about 4% and that of the 8th income decile has been about 4.3%. These are the rates at which relevant housing prices should have grown in order to sustain long run housing affordability.

5.1 Counter-factual simulations

From a policy point of view our framework suggests attending to two components of housing price inflation in order to keep it in line with the growth of the lifetime income. First is to eliminate short run housing price inflation persistence and the second is to adjust the fundamental variables. To eliminate the short run persistence various governments from time to time have imposed various measures such
as higher downpayments and additional stamp duties. In the case of Singapore, the government has introduced seven rounds of cooling measures on the property market since 2009. These measures obviously have only limited effects if actions are not taken to address the fundamentals.

We carried out a number of counter-factual simulations to see how changes in some fundamental variables would have altered the private and HDB median housing price inflation since 2007. We considered five scenarios by fixing the values for population, housing stock and user cost of housing. These have to be discussed separately for private and HDB housing.

For private housing we used total population. The growth of population is a contentious issue among Singaporeans who want to see a drastic reduction in the foreign worker population in Singapore. In 2007-08 Singapore’s resident population grew by about 1.6% while the total population grew by more than 4.9% before slowing down to about 2% in 2010-11. Restrictive immigration and work visa policies of the Singapore government are likely to slow down the population growth further. In our simulations we set the annual total population growth rate to 1.5%. To avoid an abrupt change in the simulated values, we allow the population growth rate to steadily decline over the quarters of 2007 and then onwards settle down to 1.5%. The second variable we consider is the housing stock. Singapore government has been releasing more land sites for private sector housing developments and the housing investment growth rate has increased to more than 7% in 2011 from a low of 3.8% in 2007Q1. Further increase in the housing investment growth rate is likely. We, therefore, set this growth rate to 8% in our simulation. As in the case of population growth we allow the rate to increase steadily in 2007 before settling to 8%. The third variable we consider is the user cost of housing. The key factor in the UC is the mortgage interest rate which is market determined and not subject to policy interventions in Singapore. We can, however, expect the interest rates to pick up from their rock-bottom values
presently. Our UC value for private housing stood at 6.2% in 2007Q1 and dropped to 1.7% by 2011Q4. In our simulations we set the UC value to 6.2% since 2007Q1.

As for HDB housing we used the resident population Singapore citizens and permanent residents, PRs. Despite many monetary and non-monetary incentives offered by the government, the fertility rates of Singaporeans have been falling. As a result the growth of the Singapore citizen population has slowed down to about 0.9% per year since 2005. To compensate for this the government has taken in more PRs. From 288,000 in 2000 the PR number increased to 541,000 in 2010 before declining to 532,000 in 2011. Because of the unhappiness expressed by Singaporeans on foreigner inflow, the government plan is to restrict the PR population to about 500,000. Had this been a concern in 2006 we could assume that the government would have frozen the PR population at the 2006 level of 418,000. This is a scenario we consider for our counter-factual simulation over 2007-2011. The next policy variable is the HDB housing stock. There has been a substantial slowing of the growth of HDB housing investment since the late 1990s; it declined from above 6% growth to about 0.5% growth by 2006. This effect is felt in the HDB resale market five years later because of the restriction that new units can be sold only after five years of owner occupation. The government is currently in the process of increasing the HDB housing supply substantially. For our simulation we set the housing investment growth rate to a modest 3%, the rate observed in 2001 that matters for the resale market in 2006. The third variable is UC; we set this to 2007Q1 value of 5.56%.

The simulation results are presented in Table 2. The table presents the base line simulation that we presented in Fig. 4 and 5 together with other counter-factual simulations. It presents the average annual median housing price inflation rate over 2007-2011 in each case and the price gap (actual – simulated) or the dollar amount by which the median price would have dropped by 2011Q4. Note that we obtained
the baseline simulation by removing inflation persistence from our ECM model. The other scenarios present the additional drops resulting from the adjustments to the fundamental variables.

The results in Table 2 show that the population growth policy, at least the way we have set it up, is the least effective in bringing down the housing price inflation. Obviously limiting the population growth rate requires a substantial reduction of the foreign worker population in Singapore. The results in Abeysinghe and Choy (2007) based on a comprehensive macro-econometric model show that a substantial reduction in the foreign worker population entails undesirable outcomes like reduced economic growth and high unemployment. Therefore, the foreign worker population as a policy variable for the housing market has limited flexibility. An increase in the housing stock works more effectively, more so in the HDB market. Therefore, a more desirable policy combination would be a moderate reduction in the population growth and a reasonably higher growth in the housing stock. Obviously a pick up in the user cost of housing to higher levels while the other two policies are in place may bring down the housing price inflation to affordable rates.
Table 2. Counter-factual simulations over 2007Q1-2011Q4 for median housing prices

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Annual house price inflation rate 2007-2011</th>
<th>Price gap Sin $ (Actual-Simulated) 2011Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private Housing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual</td>
<td>11.7</td>
<td>0</td>
</tr>
<tr>
<td>Simulation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base line-Fundamental, Fig. 4</td>
<td>7.01</td>
<td>$160,000</td>
</tr>
<tr>
<td>(1) Population growth 1.5%</td>
<td>6.38</td>
<td>$193,000</td>
</tr>
<tr>
<td>(2) Housing Stock growth 8%</td>
<td>5.81</td>
<td>$234,000</td>
</tr>
<tr>
<td>(3) User Cost value 6.2%</td>
<td>5.72</td>
<td>$241,000</td>
</tr>
<tr>
<td>(1) and (2)</td>
<td>5.41</td>
<td>$246,000</td>
</tr>
<tr>
<td>(1) (2) and (3)</td>
<td>4.37</td>
<td>$303,000</td>
</tr>
<tr>
<td>HDB Housing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual</td>
<td>12.37</td>
<td>$0</td>
</tr>
<tr>
<td>Simulation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base line-Fundamental, Fig. 5</td>
<td>10.41</td>
<td>$44,000</td>
</tr>
<tr>
<td>(1) PR population frozen at 418,000</td>
<td>9.50</td>
<td>$61,000</td>
</tr>
<tr>
<td>(2) Housing Stock growth 3%</td>
<td>5.10</td>
<td>$142,000</td>
</tr>
<tr>
<td>(3) User Cost value 5.56%</td>
<td>7.12</td>
<td>$108,000</td>
</tr>
<tr>
<td>(1) and (2)</td>
<td>4.31</td>
<td>$154,000</td>
</tr>
<tr>
<td>(1) (2) and (3)</td>
<td>1.23</td>
<td>$200,000</td>
</tr>
</tbody>
</table>

Note: Housing stock in this study is the accumulated housing investment. Median housing prices at 2011Q4 for private and HDB units were $1,28 mn and $456,000 respectively.

6. Conclusion

Unaffordable increases in residential property prices over a long stretch of time may entail unexpected negative socio-economic consequences. Obviously, long term housing affordability has to be assessed in relation to a measure of permanent income. The income measure proposed in this study is the lifetime income of a household. Extending from Abeysinghe and Gu (2011) we have presented a way to compute lifetime income by income deciles. If housing prices increase at the rate of lifetime incomes long term housing affordability is sustained. Otherwise, households will be burdened by excessive mortgage debts. Any increase in housing prices above this sustainable level may result primarily from a combination of two other forces, other fundamentals (e.g., supply shortfall) and expectations driven persistence of
hosing price inflation. We have presented a way to estimate the fundamental driven price level. If housing prices increase faster than the fundamental trend, housing market cooling measures are called for. The gap between fundamental and affordable trends needs to be addressed by adjusting the fundamentals.

Applying these methods to analyze Singapore residential property market reveals interesting observations. Some key results are summarized here. 1. Housing affordability measured by the price-income ratio shows a deteriorating trend across all income groups although price corrections from time to time have brought the ratio under the 30% cut-off value. Recent increases in housing prices are not as bad as the 1995-96 period when viewed from an affordability point of view. 2. With the relaxation of government restrictions on the housing market housing prices started to escalate again after 2006. Both private and HDB median prices have increased by about 12% per year over 2007-2011. When we assess how much of this is due to fundamentals, we can attribute only about 7% increase to the fundamentals in the private housing market and about 10% in the HDB market. The HBD price trend seems to be largely due to fundamentals. The gap between the actual and fundamental price can be attributed to housing price inflation expectations that need to be addressed through short term cooling measures. 3. Counter-factual simulations indicate that a moderate reduction in population growth a reasonably higher increase in housing supply can lower the housing price inflation substantially. A pickup in the mortgage interest rates will accelerate the drop in housing prices.

Acknowledgements

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