Testing For the Existence of Housing Sub-Markets In Penang, Malaysia

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ABSTRACT

This study attempts to demonstrate that residential sub-markets do exist in any geographic area by taking residential properties in Penang, Malaysia, as a case. The hedonic model was used to identify the existence of sub-markets in the study area. The model involved a clean sample of 120 house prices in 2006 and eight independent structural and locational variables. Six major areas in Penang were used to represent *a priori* spatial sub-markets in the house price model. The results showed that the sub-market variables appeared to be statistically insignificant in the hedonic model. However, results from paired-sample t-test and Chow Test showed that sub-markets did exist in Penang. This study concluded that it is insufficient to rely only on a regression model to test for sub-market existence. Instead, some appropriate diagnostic tests must be applied to the sample.

Keywords: Residential market, spatial sub-markets, hedonic modelling.

1.0 INTRODUCTION

The residential sector and the economy of a nation have a feedback relationship. A high demand for residential properties would trigger growth in many economic sub-sectors (Chin and Chau, 2003). The growth in these economic sub-sectors, in turn, will lead to the expansion of property market across wider geographic areas, especially in cities. As this process occurs over time, market segments emerge in various parts of a city with different effects on property values (Dunse and Jones, 2002; Pryce and Gibb, 2006).

One implication from the manifestation of residential market segments is the need to model property values, taking into account the possible existence of various property sub-markets. The generally accepted technique to residential property value modelling is through the use of hedonic price models. A detailed discussion of theoretical foundations and empirical development of hedonic modelling can be found in Taylor (2008). Together with the popular use of this technique in house price studies, there have been numerous studies on property sub-markets (e.g. Can, 1990; Bourassa *et al.,* 1999; Bourassa *et al.*, 2003)

For a region with a vast geographic area, property sub-markets may almost sure to exist and, thus, market segmentation can be justified (Maclennan and Tu, 1996). For a small geographic area, sub-markets may or may not exist. In such an area, property sub-markets may exist but may not be sufficiently different from each other. If, in fact, property sub-markets exist, then two important remarks can be made. Firstly, the traditional theory that says "property market is very local in nature" can be maintained. Secondly, it can be stressed that local micro factors must always be considered in any property price modelling.

This paper addresses the issue of property sub-markets by applying the hedonic model of house price using Penang as a case study. The purpose is to test the possible existence of *a priori* sub-markets in the study area. The paper is organised as follows. Section 2 reviews the literature of residential markets and sub-markets. Section 3 presents the methodology followed in this paper. Section 4 discusses the results. Finally, Section 5 concludes the paper.

2.0 LITERATURE REVIEW

2.1 Residential Sub-Markets

A residential sub-market is a component of a larger housing market (adapted from Burke and Wulff, 2007). It is a spatial set of dwellings that are reasonably close substitutes for one another within a defined geographical segment but relatively poor substitutes for dwellings in other segments. Sub-markets exist where the prices of standardized dwellings over a defined geographic area differ from those in another area. Price for equivalent residential will, however, be the same within sub-markets (Watkins, 2003).

The property price literature has criticised that sub-markets have tended to be overlooked as units for policy analysis due to the absence of reliable empirically derived boundaries. Maclennan *et al.* (1998) implied that understanding the issue of sub-markets allows housing planners to explore the geographical pattern regarding the shortfalls or pressured markets. Meanwhile, Adair *et al.* (1996) contended that sub-market modelling may help to alleviate problems of nonlinearity and interaction commonly associated with the housing markets. So, sub-markets have an impact on policy evaluation as well as on the practical side of policies related to housing (Suriatini, 2005)

The literature review suggests that residential studies at an aggregate level may cause inaccurate results in price predictions if sub-markets exist. Notwithstanding this, a study on condominiums in Penang has assumed that the properties were homogeneous with similar building attributes and neighbourhood qualities (Chin *et. al.,* 2004). In other words, it has not considered sub-market variables in the model constructed. This paper argues that this assumption was unrealistic and attempts to determine the existence of residential sub-markets across a particular geographic area in the way it was addressed by past researchers (Goodman and Thibodeau, 1998; Goodman and Thibodeau, 2003; Bourassa *et al.*, 2003; Wheeler *et al.*, 2007).

However, there is a theoretical argument that the hedonic modelling of residential properties does not require segmentation (Feitelson *et. al.*, 1996). Although this view may have some ground of reasons, in reality, market segmentation is likely to exist in most markets. This is because residential markets are not uniform entities (Adair *et. al.*, 1996). It manifests the characteristics of durability, heterogeneity and spatial fixity (Watkins, 1999). Furthermore, the residential market can be considered as a set of distinctive sub-markets arising from structural, locational and neighbourhood attributes (Adair *et. al.*, 1996). Therefore, it is unrealistic to treat residential markets in any geographical location as a single entity.

Most hedonic applications to house price analysis have treated property market as coincident with the metropolitan area and have estimated a single price function to describe equilibrium prices (Bourassa *et. al.*, 1999). The traditional models of residential market are generally predicted on the assumption that the market can be characterised by a single price-equation (Watkins, 2001). Residential markets at an overall level of aggregation are not meaningful subjects for analysis due to the existence of sub-markets in which local factors play a dominant role (McCluskey *et. al.*, 2000).

According to Watkins (2001), the earliest classification of residential sub-markets was by Straszheim (1975) in San Francisco whereby it started by subdividing the market into zones that comprised relatively homogeneous households (in racial term) and dwellings. In a study on public housing in Australia, Burke and Wulff (2007) proposed static, dynamic, and social and anthropological approaches to residential sub-market analysis, whereby various elements of demand and supply, physical and location, socio-economic, demography, and anthropology have been cited. Similar approach has also been advocated by Dacquisto and Rodda (2006).

Residential sub-markets can be identified in various ways such as spatial sub-markets, structural sub-markets and nested spatial or structural sub-markets. In Malaysia, studies by Azhari Husin and Mohd Ghazali (1994) and Hamid (2006) subdivided the residential market according to residential schemes and house price contours respectively. Meanwhile, Watkins (2001) noted that structural segmentation can be based on dwelling characteristics (Dale-Johnson, 1982), floor area and lot size (Bajic, 1985) and types of residential property, i.e. condominiums, single-family homes and apartments (Allen *et. al.*, 1995).

Some past studies recognized the importance of both spatial and structural characteristics when defining sub-markets (e.g. Watkins, 2001). In a study on Belfast residential market, Adair *et al.* (1996) subdivided the city into inner city, middle city and outer city and distinguished between terraced, semidetached and detached houses within each area. Suriatini (2005) noted that many studies have applied hedonic modelling for residential sub-market identification.

The hedonic price theory originates from Lancaster’s (1966) proposal that goods are an input in the activity of consumption, with an end product of a set of characteristics. Bundles of characteristics rather than bundles of goods are ranked according to their utility-bearing abilities. Attributes are implicitly embodied in goods and their observed market prices. The amount or presence of attributes associated with the commodities defines a set of implicit or “hedonic” prices (Rosen, 1974). The marginal implicit values of attributes are obtained by differentiating the hedonic price function with respect to each attribute (McMillan *et al.*, 1980; Triplet, 1986).

It was not until the development of Rosen's (1974) theory of implicit prices of differentiated products that the hedonic approach has been widely used as a vehicle for analyzing prices of heterogeneous economic goods. Apart from Rosen (1974), the earlier documentation such as Griliches (1961), Gordon (1973), Harrison and Rubinfeld (1978), and the later literature such as Brown and Rosen (1982), Edmonds (1984), Ohsfeldt and Smith (1984), and Epple (1987) have provided a framework of the hedonic methodology for dealing with a variety of price formation problems. The property valuation literature, in particular, has shown the application of hedonic modelling predominantly in the urban residential properties (Blomquist and Worley, 1981; Butler, 1982; Palmquist, 1984; Edmonds, 1984).

2.2 The Importance of Sub-Markets

The concept of property sub-markets is important for many reasons. It is relevant in the evaluation of urban policy mechanisms or policy implementation (Jones *et al*., 2004). For example, the literature highlights major deficiencies in understanding the impact of new housing supply due to the lack of robust empirical research at the sub-city level. Tu (2003) has contended that the existence of sub-markets, as evident in most past studies, implies that it is important to adopt the housing sub-market as a central concept in housing market analysis and a failure by housing economists to do so may lead to spurious conclusions. Although there is a possibility that sub-markets do not exist as contended by hedonic researchers such as Ekeland *et al.* (2002; 2004) and Fletcher *et al.* (2004), sub-markets seem to be an empirical issue rather than a theoretical one and, hence, deserves specific consideration. According to Ball and Kirwan (1977), in economic terms, it is usual to define a homogeneous market as one in which commodities are exchanged at uniform prices. However, they have argued that, in the case of housing, the definition must be extended to cover a uniform price structure for all the attributes of housing. This suggests that an identification of relative price serves as an indication of the existence of sub-markets.

In this context, it is argued that sub-market identification is a basic step in the hedonic modelling of residential property prices, especially to account for spatial dependence of prices (Bourassa, *et al*., 2007) and spatial heterogeneity (Bailey and Gatrell, 1995; Fik et al, 2003; Fotheringham et al, 2002; Theirault et al, 2003). Both cases have a similar implication, i.e. the same set of housing attributes may yield different profiles of housing prices in different parts of a geographic area.

2.3 Modelling Residential Sub-Markets

Although researchers in general agree with the existence of urban residential sub-markets, empirical studies differ regarding how sub-markets are specified (Yu *et al.*, 2007). Most research on residential sub-markets has employed statistical techniques such as factor analysis (Dale-Johnson, 1982); cluster analysis (Abraham *et al.*, 1994; Goetzmann and Wachter, 1995; and Hoesli *et al.*, 1997); principal component analysis (Bourassa and Hoesli, 1999); a combination of principal component analysis and other methods (Maclennan and Tu, 1996; Bourassa *et al.*, 1997; Bourassa *et al.*, 1999; Cano-Guervós *et al.*, 2003). Two recently proposed alternatives that do not involve physical boundary's discontinuities were moving windows and geographically weighted regression. Another technique used was spatially varying coefficient process models (Gelfand *et al.*, 2003). Fuzzy clustering techniques have also been proposed (Hwang and Thill, 2005).

In this paper, we adopted the simplest and most traditional technique, namely dummy variables, to identify residential sub-markets, besides paired-sample t-test and Chow test for differing sample means.

As an illustration of the use of dummy variables, the hedonic model can be specified to relate the market values of properties to their attributes as follows:

$$P = X\beta + \varepsilon \qquad (1)$$

where P is an (n x 1) column vector of property value; X is an (n x m) vector of property attributes; β is an (n x 1) column vector of hedonic prices of property attributes; and ε is an (n x 1) column vector of error term.

Property attributes include structural and locational factors. Structural factors are such as floor area and building conditions. Locational factors include distance from Central Business District. Significant existence of a spatial sub-market can be detected by including a dummy variable to represent the area in the model. However, this would be the most simplistic detection of sub-market and should be supported by other tests such as paired sample t-test and chow test.

Shifter factors such as locational differences tend to cause different market profiles of a particular real estate type. As a matter of fact, market profiles can be different on the basis of any discriminating factor such as time period, real estate type, price range, demographic characteristics, etc. In the statistical terms, the differing profiles are reflected in the differing regression hyper surfaces (see Hamid, 1993).

Let say, we have a simple property price model as follows:

$P_i = \alpha + \beta X_i + u_i$ (2)

where P_i is the i^{th}. observation of property price and X_i is the i^{th}. observation of property attribute; α is regression intercept and β is regression slope.

For a particular discriminating factor, any of four situations can prevail pertaining to two groups that are being compared (Figure 1). Situation 1 is where the regression intercept between the two groups is the same and so with the slope, by assumption. Situation 2 is where the regression intercepts between the two groups are different and so with the slopes. Situation 3 reflects a situation where the regression intercept between the two groups is the same but the regression slopes are different. Situation 4 reflects a situation where the regression intercepts and slopes are different between the two groups.

In general, three common techniques can be adopted to investigate the above situations. Firstly, to estimate different regression models for different groups with respect to the discriminating factor (e.g. different models for different locations) and then to analyse the regression outputs to ascertain whether or not the regression hypersurfaces are significantly different from each other. This will not be taken up in this paper due to limited sample size.

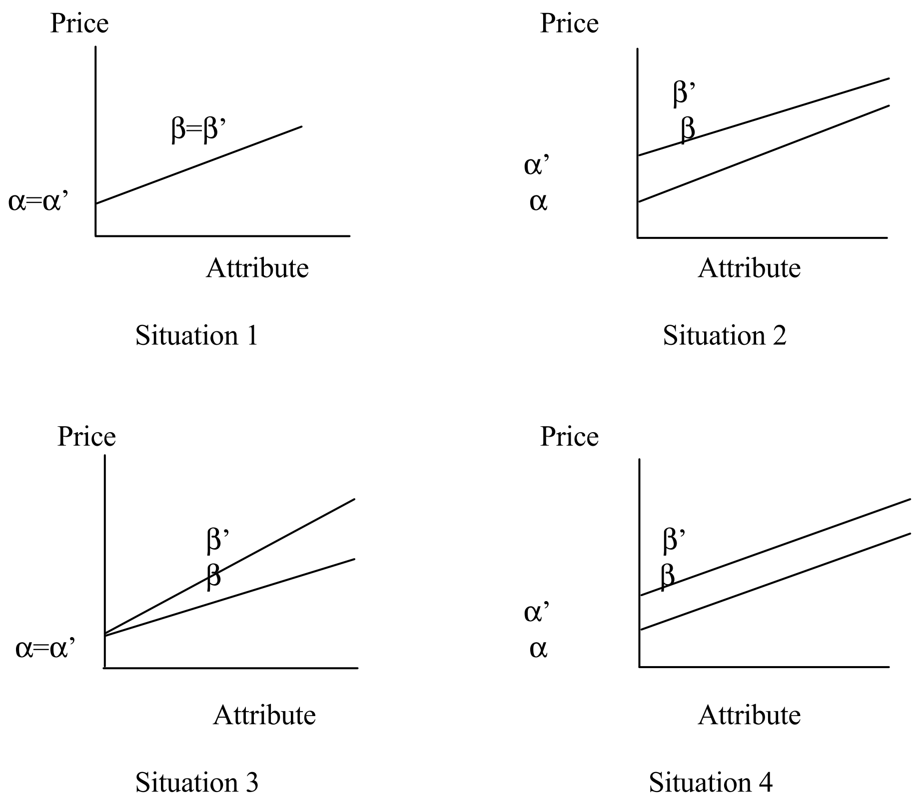

Figure 1: Situations of regression profiles among localities (represented by lines)

Secondly, to introduce dummy variables for such a factor with D = m-1, where D is the number of dummy variables to be included in a model and m is the number of discriminated groups with respect to a discriminating factor under question, namely property sub-markets in our case. [ζ]

[ζ] The general rule for specifying dummy variable is discussed in many econometrics textbooks. See for example, Gujerati (1979), pp. 209-291.

Let's specify a simple model as follows:

$$P_i = \alpha + \lambda X_i + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{3i} + u_i \qquad (3)$$

where P and X are as defined earlier; D is a dummy variable representing property sub-markets, namely D_1 for sub-market 1, D_2 for sub-market 2, D_3 for sub-market 3; α, λ, β's are the regression estimates; and u is error term. Since dummy variables are expressed as 1,0 variables, we can compute the following identity pertaining to the discriminating sub-markets: $D_{1i} + D_{2i} + D_{3i} = 1$. Let's take $D_{1i} = 1 - D_{2i} - D_{3i}$ (which means taking sub-market 1 as a control group) and substitute this into equation (3) to give the following expression:

$$P_i = \alpha + \lambda X_i + \beta_1(1-D_{2i}-D_{3i}) + \beta_2 D_{2i} + \beta_3 D_{3i} + u_i \qquad (4)$$

Expanding and re-arranging equation (4) will then give the following expression:

$$P_i = (\alpha + \beta_1) + \lambda X_i + (\beta_2 - \beta_1)D_{2i} + (\beta_3 - \beta_1)D_{3i} + u_i \qquad (5)$$

Since we use D_1 as a control group, in equation (5), the regression intercept contains a quantity that represents property sub-market 1, namely β_1. The regression slopes tell how much the intercepts of property sub-markets 2 and 3 differ from the intercept of property sub-market 1, which can be readily checked – assuming $E(u_i)=0$ – as follows:

$$E(P_1|D_{2i} = D_{3i} = 0, X_i) = (\alpha + \beta_1) + \lambda X_i \qquad \text{(sub-market 1)} \qquad (6)$$

$$E(P_2|D_{2i} = 1, D_{3i} = 0, X_i) = (\alpha + \beta_2) + \lambda X_i \qquad \text{(sub-market 2)} \qquad (7)$$

$$E(P_3|D_{2i} = 0, D_{3i} = 1, X_i) = (\alpha + \beta_3) + \lambda X_i \qquad \text{(sub-market 3)} \qquad (8)$$

Equations (6) through (8) assume that the slope of regression equation for one locality, λ, is the same with that of other localities (situation 1 or 4 in Figure 1). However, situation 1 will only occur if and only if $\beta_1=\beta_2=\beta_3=0$, which is quite unlikely. Therefore, equations (6) through (8) most likely represent situation 4 in Figure 1.

If we want to test for the similarity in the slope, we should introduce another set of dummy variables. Let's modify equation (3) as follows:

$$P_i = \alpha + \delta X_i + \lambda_1 X_i D_{1i} + \lambda_2 X_i D_{2i} + \lambda_3 X_i D_{3i} + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{3i} + u_i \qquad (9)$$

Working out in the similar fashion described above will give the following equation:

$$P_i = \alpha + \delta X_i + \lambda_1 X_i(1-D_{2i}-D_{3i}) + \lambda_2 X_i D_{2i} + \lambda_3 X_i D_{3i} + \beta_1(1-D_{2i}-D_{3i}) + \beta_2 D_{2i} + \beta_3 D_{3i} + u_i \qquad (10)$$

Expanding and re-arranging equation (10) will give the following equation:

$$P_i = (\alpha + \beta_1) + (\delta + \lambda_1)X_i + (\lambda_2 - \lambda_1)X_i D_{2i} + (\lambda_3 - \lambda_1)X_i D_{3i} + (\beta_2 - \beta_1)D_{2i} + (\beta_3 - \beta_1)D_{3i} + u_i \qquad (11)$$

Assuming $E(u_i)=0$ in equation (1), the expected property market profiles in different sub-markets can now be computed as follows:

$$E(P_1|\, D_{2i} = D_{3i} = 0, X_i) = (\alpha + \beta_1) + (\delta + \lambda_1)X_i \qquad \text{(sub-market 1)} \qquad (12)$$

$$E(P_2|D_3 = 0, D_2 = 1, X_i) = (\alpha + \beta_2) + (\delta + \lambda_2)X_i \qquad \text{(sub-market 2)} \qquad (13)$$

$$E(P_3|D_2 = 0, D_3 = 1, X_i) = (\alpha + \beta_3) + (\delta + \lambda_3)X_i \qquad \text{(sub-market 3)} \qquad (14)$$

Equations (12) through (14) assume that the intercept as well as slope of regression equation for one locality differ from those of other localities (situation 2 in Figure 1). Since each of situations 2 and 4 demands slightly different model specifications and testing, only situation 4 will be investigated in this paper. This indicates the opportunity to investigate and test the other three situations in future studies.

In assigning sub-market dummy variables, it is assumed that residential markets in the study area can be defined *a priori* based on a combination of socio-economic or environmental characteristics (Schnare, 1980; Harsman and Quigley, 1995; Vandell, 1995; Malpezzi, 2003), and political or geographic boundaries (Schnare and Struyk, 1976; Goodman and Kawai, 1982; Adair *et al.*, 1996). The result from such an approach to segmentation is reflected in Figure 2.

The third technique for investigating differences or similarity of regression profiles is using the modified Chow test. This test examines the equality of regression hyper surfaces of different models. The formula is (Watkins, 2001):[1]

$$F^* = \frac{(SSR_c - (SSR_1 + SSR_2))}{(SSR_1 + SSR_2)} \times \frac{((N_1 + N_2) - (K_1 + K_2))}{\text{Min}(K_1, K_2)} \tag{15}$$

where; SSR_1, SSR_2 and SSR_c are the sum of squared residuals for the individual models and the combined model and N_1, N_2 and K_1, K_2 are the number of observations and number of parameters in the individual models respectively.

The F* is then compared with the theoretical $F_{\alpha;\, v1,\, v2}$, where $v_1 = K$, $v_2 = n_1 + n_2 - 2K$. The decision is that, if $F^* > F_{\alpha;\, v1,\, v2}$, then the H_0 hypothesis will be rejected. If the result is the reverse, H_1 will be accepted. Rejection of H_0 will bring us to a conclusion that price-attribute relationship is different among localities.

3.0 DATA AND METHOD

3.1 The Study Area and Data

Dubbed as the Pearl of Orient, Penang is the second smallest state in Malaysia. Situated on the north-west coast of Peninsular Malaysia, at the upper part of the Straits of Malacca, the island spans about 293 square km across. It has a total population of about 1.2 million people. With about 2,032 people per sq. km. it has the highest population density in Malaysia.

The area was chosen for this study since it has been previously considered by Chin and Chau (2003) and Chin *et al.* (2004) but without sub-markets variables. The sample used in this study comprised 180 sale records of single-storey to three-storey terraced houses transacted between June 2006 and December 2006. The properties, located within six major urban areas in Penang (Figure 2) were sorted

[1] Alternatively, the classical Chow test can be applied with a slightly different result. The formula is:

$$F^* = \{[\Sigma e^2_p - (\Sigma e^2_1 + \Sigma e^2_2)]/K\}/\{(\Sigma e^2_1 + \Sigma e^2_2)/(n_1 + n_2 - 2K)\}$$

where Σe^2_p is sum squared errors (SSE) for the pooled sample; Σe^2_1 is SSE for sample 1; Σe^2_2 is SSE for sample 2; K is number of parameters including the intercept; n_1 is the size of sample 1; and n_2 is the size of sample 2. [For a simple discussion on the Chow test, consult Koutsoyiannis, 1986, pp. 164-168.]

out from the original data set. The final cleaned data set comprised a total of 120 single-storey terraced and double-storey terraced houses only.

This study involved the gathering of both primary and secondary data (Table 1). The primary data were associated with distance variables whilst the secondary data were related to property transactions. Observations were made to determine property distance from the Central Business District (CBD), shopping complexes, premier schools and industrial area. Property transaction data for the study were obtained from Raine & Horne International Zaki and Partners Sdn. Bhd., Penang. Besides, census data and other information were obtained from the Department of Statistics Malaysia, site survey, and maps.

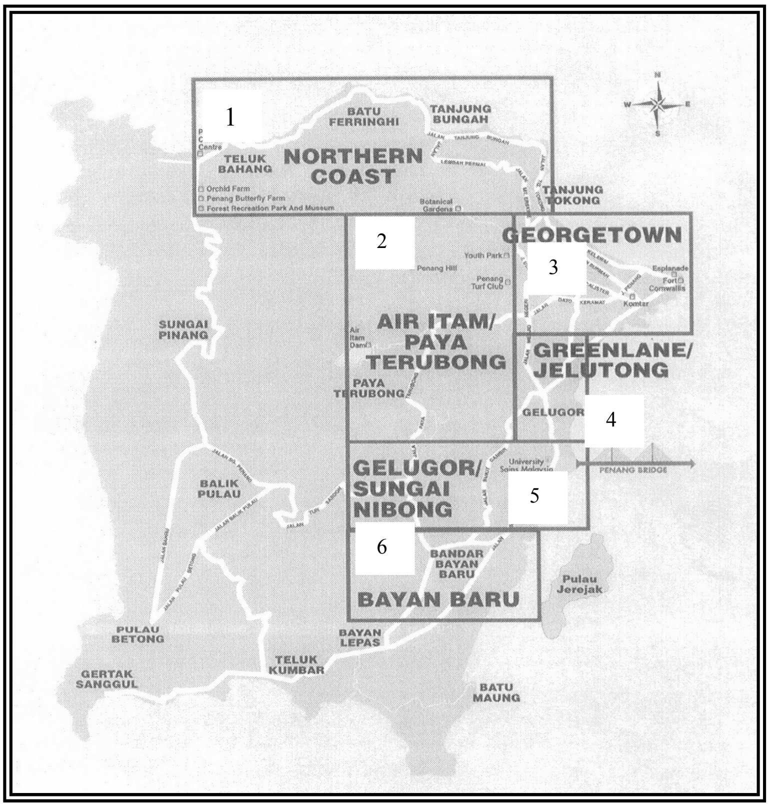

Figure 2: Six major development areas in Penang (Chin *et al.*, 2004**)**

Table 1: Source of Data

Type of Data	*Data*	*Source*
Primary	Distance from CBD, nearest shopping complexes, premier school and industrial area	Map
Secondary	Property transaction data (sale price, address, land area, floor area, number of bedrooms, types of property, and types of lot)	Raine & Horne International Zaki and Partners Sdn. Bhd.
	Census data (composition of ethnic groups)	Department of Statistics Malaysia

3.2 The variables and their measurements

Twenty-five independent variables representing locational, neighbourhood and structural attributes were selected to be included in the hedonic model. The list of variables and their expected signs are shown in Table 2.

Table 2: The Variables, their Details and Expected Signs

Attributes	*Definition*	*Variable label*	*Scale*	*Expected Sign*
Dependent Variable	Price (RM / unit)	*PRICE*	ratio	
Physical	Land Area (m^2)	*L_AREA*	Ratio	+ve
	Floor Area (m^2)	*BUILT*	Ratio	+ve
	Number of Bedrooms	*B_ROOM*	Ordinal	+ve
	Intermediate Lot	***INTER***	Dummy	Control
	End Lot	*END*	Dummy	+ve
	Corner Lot	*COR*	Dummy	+ve
	Single-Storey Unit	***STOREY_1***	Dummy	Control
	Double-Storey Unit	*STOREY_2*	Dummy	+ve
	Freehold Unit	*FREEHOLD*	Dummy	Control
	Leasehold Unit	*LEASEHOLD*	Dummy	-ve
	Neighbourhood Size (m^2)	*NHOOD*	Ratio	?
Locational	Distance from Central Business District (km)	*CBD*	ratio	
Neighbourhood	Proximity to shopping complex (km)	*SHOP*	Ratio	
	Proximity to premier school (km)	*SCHOOL*	Ratio	
	Proximity to industrial area (km)	*INDUSTRY*	Ratio	
	Malay (%)	***MALAY***	Ratio	
	Chinese (%)	*CHINESE*	Ratio	
	Indian (%)	*INDIAN*	Ratio	
	Others (%)	*OTHERS*	Ratio	
Development areas	Northern Coast	*N_COAST*	Dummy	?
	Air Itam	*A_ITAM*	Dummy	?
	Georgetown	***G_TOWN***	Dummy	Control
	Greenlane/Jelutong	*G_LANE*	Dummy	?
	Gelugor/Sungai Nibong	*S_NIBONG*	Dummy	?
	Bayan Baru	*B_BARU*	Dummy	?

*Note: * Question mark (?) indicates uncertain coefficient sign of the variable involved. Texts in bold represent the standard property*

Residential physical attributes specified in the model were land area, floor area, number of bedrooms, lot position (intermediate, end, or corner), types of interest (freehold, leasehold), and neighbourhood size. Data on all of these variables were obtained together with the transaction data.

Neighbourhood size was included in the model because it was perceived to have an effect on the size of property supply; the bigger the size, the more is the supply. Property supply, in turn, may affect property price in a certain way within a particular neighbourhood.

Distance to the Central Business District (CBD) was measured as a straight-line distance of a particular residential property from the Tun Abdul Razak Complex (KOMTAR). For properties located further away from CBD, they can be expected to have lower prices, the coefficient for this variable was expected to be negative.

Neighbourhood attributes were expressed in terms of property distance to the nearest shopping complex, proximity to premier schools, and proximity to industrial areas. Distance from shopping complex, namely KOMTAR, Perangin Mall, Island Plaza, Gurney Plaza, One-Stop Midlands Park, Queensbay Mall, COSMART, Sunshine Square and Sunshine Farlim, was measured as property distance from any of these major shopping complexes within a two-km radius. Residential properties located within a two-km radius from any shopping complex were assigned the value of 1, otherwise it was 0. The coefficient for this variable was expected to be positive.

According to Chin *et. al*. (2004), proximity to a reputable or premier school may increase residential property values. Hence, the coefficient for this variable was expected to be positive. Property proximity to any of the premier schools, namely Penang Free Secondary School, Convent Greenlane Secondary School and St. George Secondary Girl School, was measured within a two-km radius. Properties within this radius were assigned a value of 1, otherwise 0.

Property distance from the Bayan Lepas Industrial Area (which consists of Free Trade Zone and Non-Free Trade Zone) was also measured within a two-and-a-half-km radius. Residential properties located within this radius were assigned a value of 1, otherwise 0. The coefficient for this variable was expected to be negative.

Demographic characteristics of the study area were also included in the model. In particular, the composition of ethnic groups may influence property prices within a defined geographic area. However, the coefficients for these variables cannot be ascertained *a priori*.

Market variables included in this study were defined as a spatial dimension the proxy of which was geographic area. According to Chin *et. al.* (2004), Penang Island is divided into six major geographic areas, namely Northern Coast, Georgetown, Air Itam / Paya Terubong, Greenlane / Jelutong, Sungai Nibong / Gelugor and Bayan Baru (Figure 2).

3.3 The Modelling Steps

The transactions data obtained from Raine & Horne International Zaki + Partners Sdn. Bhd. were first analysed to ensure sufficiency of information. Secondly, the data were given numerical measurements to enable regression analysis using the Statistical Package for Social Sciences software. Thirdly, paired-sample t-test was applied to compare the means of property prices located in different geographic areas. Fourthly, correlation analysis was carried out to detect multicollinearity in the hedonic model. Fifthly, regressions using all the specified variables as shown in Table 2 were run. Finally, statistical diagnostic tests were undertaken to evaluate the statistical quality of the estimated hedonic model. The model was also compared to other house price models from Malaysia to support the discussion.

4. RESULTS AND DISCUSSION

The descriptive statistics of both dependent variable and selected independent variables are presented in Table 3. The properties, including the single- and double-storey terraced residences in the study area were priced between RM160,000 and RM880,000 with the standard deviation of approximately RM130,064. The results indicate that the land area and floor area of the sampled properties were in the range of 968.54 to 4,944.84 sq. m. and 792.33 to 4,107.94 sq. m., respectively. The means of land area and floor area were 1,790.94 sq. m. and 1,519.60 sq. m., respectively, reflecting an 84.8% of building to land ratio. With that range of size, the per unit mean price of properties was RM 422,692.50.

The largest ethnic group in the study area were Chinese, followed by Malay, Indian, and other ethnics.

4.1 Diagnostic Tests

Multicollinearity test was carried out on the independent variables. The test has revealed some "problematic" variables such as proximity to industrial areas, proximity to premier schools, and percentage of the ethnic.

Three types of functional forms - linear, semi-log and log-log - were tested to determine the most appropriate model to use for further analysis (Table 4). On the basis of R^2, adjusted R^2, and F-value, it is clear that the linear regression model has produced the best result. Therefore, it was chosen for further analysis.

Table 3: Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation
PRICE	120	720,000.00	160,000.00	880,000.00	422,692.50	130,063.81
L_AREA	120	3,976.30	968.54	4,944.84	1,790.94	640.52
BUILT_AREA	120	3,315.61	792.33	4,107.94	1,519.60	557.01
NEIGH_SIZE	120	27,879,600.35	3,600,083.10	31,479,683.45	21,432,857.58	7,999,594.16
BED_ROOM	120	3.00	2.00	5.00	3.36	0.53
CBD	120	12.34	1.30	13.64	6.38	3.32
INDUSTRY	120	1.00	0.00	1.00	0.31	0.46
SHOP	120	1.00	0.00	1.00	0.57	0.50
SCHOOL	120	1.00	0.00	1.00	0.4167	0.50
N_COAST	120	1.00	0.00	1.00	0.10	0.30
G_TOWN	120	1.00	0.00	1.00	0.13	0.34
A_ITAM	120	1.00	0.00	1.00	0.12	0.32
G_LANE	120	1.00	0.00	1.00	0.15	0.36
S_NIBONG	120	1.00	0.00	1.00	0.31	0.46
B_BARU	120	1.00	0.00	1.00	0.19	0.40
INTER	120	1.00	0.00	1.00	0.77	0.42
COR	120	1.00	0.00	1.00	0.18	0.38
END	120	1.00	0.00	1.00	0.06	0.24
FREEHOLD	120	1.00	0.00	1.00	0.94	0.24
LEASEHOLD	120	1.00	0.00	1.00	0.06	0.24
STOREY_1	120	1.00	0.00	1.00	0.33	0.47
STOREY_2	120	1.00	0.00	1.00	0.67	0.47
MALAY	120	74.86	0.45	75.31	29.56	15.81
CHINESE	120	80.18	18.04	98.22	60.54	16.14
INDIAN	120	10.94	1.28	12.22	9.28	1.60
OTHERS	120	1.87	0.06	1.93	0.62	0.42

Table 4: Summary of Models' Basic Statistics

	Linear	*Semi-Log*	*Log-Log*
R^2	0.796	0.576	0.589
Adj. R^2	0.572	0.506	0.521
F-value	10.364	8.157	8.610
Standard Error of Estimate (SEE)	85,066.57	0.22384	0.22035

4.2 Regression results and evidence of Sub-markets

Hedonic modelling of the data from the study area that has used linear functional form produced results as shown in Table 5. The model was able to explain 79.6% of the variation in the property prices in the study area. In addition, the F-value indicates that the model as a whole significantly explains the variation in the residential property prices in the study area.

As indicated in Table 5, land area was a significant determinant of residential property prices. A unit increase in land area has caused RM104 increase in the property price. Type of property was also found to be a good variable in explaining the variation in property price. The unstandardized regression coefficient indicates that the mean price of a double-storey terraced house could have been about RM109,502 higher than that of the single-storey terraced house. The mean prices of other ethnic groups' residences could have been about RM150,897 higher than those of the Malay and Chinese, taken on average.

In order to determine the significant existence of spatial sub-markets in the study area, evaluation has been made based on the regression coefficient, paired-sample t-test and modified Chow test.
Based on the results in Table 5, none of the sub-market variables has a significant t-value and, thus, one may conclude that there was no significant sub-market existence in Penang property market. The results have reflected either situation 1 or 3 in Figure 1. However, the paired-sample t-test for the means of residential prices has indicated that at least some property sub-markets could have existed in some parts of Penang (Table 6). The outcomes reveal that the mean property prices in the rest of Penang island were different from the mean of property prices in the following pair-wisely combined geographic areas: Northern Coast (Mean_1) and Sungai Nibong (Mean_5); Northern Coast (Mean_1) and Bayan Baru (Mean_6); George Town (Mean_3) and Sungai Nibong (Mean_5); Air Itam (Mean_2) and Sungai Nibong (Mean_5); Greenlane (Mean_4) and Sungai Nibong (Mean_5); Sungai Nibong (Mean_5) and Bayan Baru (Mean_6). Then, this phenomenon could have reflected either situation 2 or 4 in Figure 1.

Table 5: Regression Results Based on Linear Model

R^2	0.796			0.593		
Adj. R^2	0.572			0.578		
F	10.364			14.599		
SEE	85,066.567			84,461.249		
N	120			120		
	With segmentation			Without segmentation		
Variable	*Coefficient*	*t-value*		*Coefficient*	*t-value*	
Constant	208,226.35	2.207	**	205,931.48	2.429	**
Land Area (m^2)	104.45	5.783	**	102.25	5.887	**
Floor area (m^2)	1.06	0.068		-2.23	-.148	
Neighbourhood Size	0.00	1.432		0.00	2.791	**
Number of bedrooms	-23,207.38	-1.445		-18,524.43	-1.187	
Distance from Central Business District (km)	-1,615.23	-0.240		-6,516.34	-2.306	**
Proximity to shopping complex (km)	3,499.00	0.149		6,682.80	0.335	
Lot position (Corner)	24,472.95	0.871		24,234.28	0.879	
Lot position (End lot)	29,902.36	0.778		33,042.04	0.876	
Tenure (Leasehold)	-71,947.03	-1.901	*	-74,371.16	-2.027	**

Type of property unit (double-storey terraced)	109,502.22	5.116	**	119,638.80	6.478	**
Percent of Indian Ethnic	-10,987.17	-1.232		-5,893.53	-0.786	
Percent of Other Ethnics	150,896.82	1.980	**	55,518.51	1.992	**
Sub-market 1 (Northern Coast)	-143,374.54	-1.448		-	-	
Sub-market 2 (Air Itam)	1,850.99	0.030		-	-	
Sub-market 4 (Greenlane/Jelutong)	-24,667.00	-0.660		-	-	
Sub-market 5 (Gelugor/Sungai Nibong)	-4,883.71	-0.115		-	-	
Sub-market 6 (Bayan Baru)	-49,021.62	-0.729		-	-	

*** Significant at 5% and better; * Significant at 10%.*

Since the paired-sample t-test was a non-parametric test, it was further corroborated with the modified Chow test (Table 7), whereby there was further evidence of differing regression hypersurfaces of residential property prices in Penang. This implies that different property sub-markets could have existed in Penang. The results in Table 7 imply that situation 2, 3, or 4 of Figure 1 could have been the case in the study area.

Table 6: Paired-Sample t-test Results

	Mean_1	Mean_2	Mean_3	Mean_4	Mean_5	Mean_6
Mean_1	-	-	-	-	-	-
Mean_2	-1.534	-	-	-	-	-
Mean_3	-0.201	-	1.377	-	-	-
Mean_4	-1.426	-1.255	0.200	-	-	-
Mean_5	-4.302**	-4.151**	-2.539**	-2.836**	-	-
Mean_6	-1.993**	-1.822*	-0.282	-0.511	2.368**	-

*** Significant at 5%; * Significant at 10%.*
Mean_1 = Mean property prices for Northern Coast, Mean_2 = Mean property prices for Air Itam, Mean_3 = Mean property prices for Georgetown, Mean_4 = Mean property prices for Greenlane, Mean_5 = Mean property prices for Sungai Nibong, Mean_6 = Mean property prices for Bayan Baru

Table 7: Results of the modified Chow Test

Segments	*Modified Chow test*
Sungai Nibong/Gelugor/Bayan Baru with Northern Coast/Georgetown	3.56
Sungai Nibong/Gelugor/Bayan Baru with Air Itam/Paya Terubong/Jelutong/Greenlane	4.54
Northern Coast/Georgetown with Air Itam/Paya Terubong/Jelutong/Greenlane	7.10

Tabulated F-value at 5% significant level = ___

However, when the results in Tables 5, 6, and 7 are considered together, we can come to a conclusion, that is, at least the intercept or the slope was different so that any one situation in Figure 1 could have reflected in the results. However, by giving more weights to the results in Tables 5 and 7, the most possible situation in the study area could have been represented by situation 3 as shown in Figure 1. This situation tells that the basic property value could have been the same for all areas, but prices may start to change spatially as one looks for a property from one place to another on the island.

The comparison between regression result with and without sub-market variables depicts that the model without sub-market variables was marginally better than the model with sub-market variables in terms of adjusted R^2, F-test and Standard Error of Estimate (SEE).

From the regression result without sub-market variables, it was found that land area, distance from CBD, neighbourhood size, interest in property, types of property and other ethnic group were significantly affecting residential property prices in Penang. Some of these variables were found to be insignificant in the model which incorporated sub-market variables such as distance from CBD, neighbourhood size and interest in property. This means, these variables were significant in explaining the variation in property price but the inclusion of sub-markets variables has produced less accurate outcome. This is evident when the value of adjusted R^2, F-test and SEE shows that the model without sub-markets variables was better compared to that with sub-market variables.

The regression results for neighbourhood size in the model without sub-market variables shows that a higher supply of properties can increase the price of properties in a particular area. The sign of this variable was not as expected. This may be caused by inaccurate data. In the recent years, there have been land reclamation activities carried out on Penang Island. However, the data on neighbourhood size after land reclamation were not available. The same model also illustrates that changes from freehold to leasehold could have significantly reduced property prices about RM74,000.

Distance from CBD was found to be insignificant when the sub-markets variables were included in the model. This may be due to the relationship between the sub-market variables and distance from CBD. This statement is made because distance from CBD was found to be significant in the regression result without sub-market variables. In addition, the effects of shopping complex on residential property prices were very little and this outcome was also in contrast to the previous studies carried out in Penang. Previous studies conducted in Penang used transacted data from 1996 to 1998 while this study used properties transacted in 2006. During this period, there have been a number of new shopping complexes entering the market, such as Queensbay Mall. This means that more and more properties in the study area could have now been located within a 2-km radius distance from shopping complexes compared to properties in the previous study. Hence, proximity to shopping complex has been improved compared to the past.

Statistical testing had been carried out to evaluate the quality of the hedonic model constructed. This has been supported by comparing the model's performance with those past studies conducted in Malaysia.

From Table 9, it can be seen that the F-test for this study was low compared to the previous studies conducted in Malaysia. Perhaps, this was caused by the independent variables selection. Based on the literature review, it was found that the studies with a greater F-value took into account of the structural quality of property such as building condition, finishes, renovations and so on whilst the study ignoring the structural quality has lower F-value. This study did not take building structural quality into consideration. However, the F-value of this study was greater than that of the study that ignored structural quality by Hamid (2006). Moreover, the study by Hamid (2006) also employed linear regression model, the same as this study. This means that this model was good compared to that conducted by Hamid (2006) on the basis of F-value.

Table 9: Comparison of F-test and adjusted R^2

No.	*Study*	*Adjusted R^2*	*F-statistics*
1.	Hamid (2006) [2]**	70.4	6.938
2.	Hamid and Chin (2006) ***	92.5	141.731
3.	Chin et al (2004)*	69.5	43.97
4.	Chin & Chau (2003)	75.1	60.68
5.	Dzurllkarnain Daud et al (1996)*	93.5	260.931
6.	Azhari Husin and Mohd Ghazali (1994)*	96	140.512
7	Aminah Yusuf (2006)	Not reported	Not reported
8	This study	57.5	10.764

[2] The F-statistics refers to per unit residential price. F-statistics for per sq ft price is not taken into consideration

* *Detailed structural variables included in the model. ** GIS was applied in linear distance measurement. *** Detailed structural variables and GIS were used.*

Table 9 indicates that past studies have either included detailed structural variables or used a geographic information system (GIS) to measure distance. The results also show that the adjusted R^2 obtained in this study was the lowest compared to other studies conducted in Malaysia. This maybe caused by the unavailability of structural variables in this study and, thus, exclusion of structural variable in the model. As stated above, most of the studies conducted by past researchers considered detailed structural variable.

As for distance-based variables, the use of mapping observation may be inferior to the GIS method used in Hamid (2006). The less accurate distance measurement may have produced poorly measured distance and hence reduced the adjusted R^2 obtained in this study.

The same table also suggests that both studies of Penang that use similar variables and method of distance measurement have greater adjusted R^2 than this study. This maybe due to the use of different property types. Perhaps, it is essential to include detailed physical characteristics for the construction of hedonic model for residential properties in Penang.

5.0 CONCLUSION

The main objective of the study was to identify the existence of residential sub-markets in Penang property market. A number of analyses have been carried out. The hedonic modelling was carried out on the data by using SPSS. The regression model showed insignificant sub-market variable.

In the model, distance from CBD was found to be insignificant when sub-markets variables were taken into consideration. However, distance from CBD was found to be significant when sub-markets variables were ignored. This suggests that the proxies for sub-market variables were related to distance. Correlation analysis has proved the relationship between distance from CBD and sub-markets variables. Proximity to shopping complex was not significant maybe because there was addition of new shopping complexes in the market wherein most of the properties were located near to shopping complexes.

Although this study has produced findings that will be academically beneficial, the study was limited in a number of aspects which could be addressed in future research. Future research can be conducted on various types of property using other variables which are ignored in this study such as the detailed physical variables. It can also use GIS to undertake distance measurement for the purpose of spatial variable construction. Besides that, further research can consider other than the spatial dimension in testing the existence of residential sub-markets.

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