URBAN REAL ESTATE
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A way to understand housing markets beyond "Subsidy, Gap and Market"

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Contents

1. Background to the report

This is a **working** document that attempts to consolidate a number of research initiatives investigating how one can better undertake a housing market study. It is not intended to present a final set of results or to put forward a definitive methodology, but rather it is an attempt to describe a research process and to propose a methodology that can stimulate discussion and attract critical response. As a result, comments would be most welcome.

The report draws extensively on the following research:

Hogarth, K., 2015, *Analysis of the Cape Town Housing Market: Supply, Demand and Housing Submarkets*, City of Cape Town.

Lendor, B., Ndiziba, N., and Oertel, M. 2015, *The Propensity of Different Households to Demand Certain Housing Types in Cape Town*. MSc. Property Studies Honours Thesis. UCT.

Acknowledgement is also given to:

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2. Introduction

The current housing delivery model in South Africa is generally seen as problematic for the following reasons. Firstly, both public and private housing delivery is failing to sufficiently address the housing backlog and cater for new household growth (FFC, 2012). From the public perspective, this is due to an increasing fiscal constraint and insufficient delivery capacity; whereas the formal private sector has failed, for the most part, to deliver housing stock that is affordable to large segments of the population. Secondly, the housing delivery model has reinforced the inefficient, inequitable and unviable nature of our cites due to the poor location and low densities that characterise many housing developments in South Africa. Lastly, the model, due to a plethora of regulations and standards, historical inertia and the need for equity and economies of scale, tends to produce relatively standardised products that fail to match the diversity of household types.

This is particularly problematic when it comes to understanding the needs of the growing “gap market”, which has been lumped into a single market segment defined on the bottom end of the scale by the R3500 maximum monthly household income eligible for state subsidy, and on the top end of the scale by the household’s ability to access credit to purchase a unit in the bonded market, which is currently estimated at between R15 000 and R20 000 monthly household income. It stands to reason that the purchasing power within this broad band of household income varies greatly, yet the demand is generally seen as homogeneous across this band. Furthermore, the diverse characteristics of the households themselves (including, size, age, life stage etc.) and how those characteristics shape the demand for a particular housing product is seldom, if ever, considered. It is therefore not surprising that the market response and state intervention in the “gap market” has been relatively unsuccessful.

Many factors have been touted as being responsible for this, although one, which has largely been overlooked, and is arguably of paramount importance, is the lack of a nuanced understanding of the nature of demand for housing. So far, the housing delivery model appears to have assumed a homogeneous group of consumers, with only a cursory regard for household income as a proxy for demand.

There is a need for the state and market to deliver housing that better matches the needs, preferences and purchasing power of households. In short, there is a need for a far better understanding of what housing and households look like in South Africa.

Conducting a comprehensive and nuanced submarket analysis (avoiding over-simplified ‘market segments’ such as Subsidy, Gap and Market) is important to firstly, identify and track the drivers of demand, and better understand housing market dynamics, for example the filtering of housing stock from higher income to lower income households over time, and households climbing the ‘property ladder’. Secondly, to more accurately estimate the quantity and nature of housing units that will be demanded in the future, by projecting household growth and housing choices per submarket. Thirdly, to identify shortages or surpluses in specific submarkets, enabling more appropriate and effective intervention.

As a result, the purpose of this paper is to outline a methodology of how the South African housing market could be segmented and disaggregated into a set of inter-related sub-markets. To begin with, the paper outlines the proposed methodology and then systematically discusses each stage of the process followed.

3. Methodology outline

STEP 1:

THEORETICAL BASIS
CONSUMER CHOICE THEORY

STEP 2:

SEGMENT & DISAGGREGATE THE MARKET BASED ON SINGLE ATTRIBUTES

STEP 3:

SEGMENT & DISAGGREGATE THE MARKET BASED ON SINGLE HOUSEHOLD ATTRIBUTES OVER DIFFERENT PERIODS

STEP 4:

ANALYSE RESULTS

PROPENSITY OF DEMAND | GAP ANALYSIS

STEP 5:

SEGMENT & DISAGGREGATE THE MARKET BASED ON MULTIPLE ATTRIBUTES

CLUSTERING | DECISION TREE

STEP 6:

ANALYSE RESULTS

PROPENSITY OF DEMAND | GAP ANALYSIS

STEP 7:

ASSESS FUTURE DEMAND BASED ON DEMOGRAPHIC PROJECTIONS

4. Theoretical basis – Step 1

The theory of housing demand has its basis in consumer choice theory, which is concerned with how a rational consumer makes consumption decisions. The theory states that each consumer will try to reach the highest possible level of satisfaction/utility and consumers will realise this utility from the bundle of attributes possessed by a good and will trade these off against the bundle of attributes of another good (Lancaster, 1990). Lancaster (1990) importantly highlights that a good itself does not give rise to utility, but the attributes of the good do. However, while demand is driven by a consumer’s needs and preferences, the choice is constrained by the affordability and availability of the good. Therefore, a consumer will choose the good with a particular set of attributes that is available, affordable and results in the highest level of utility being achieved.

However, as both households and houses are heterogeneous in nature and possess different bundles of characteristics and attributes, a series of sub-markets exist (Galster, 1996). A sub-market is a grouping of households and houses that share a unique and common set of attributes. The key-defining feature of a sub-market is whether each household in the group can be substituted with each other in terms of the attributes they possess. Similarly, houses in a particular sub-market must be substitutes for each other in terms of the characteristics they possess (Galster, 1996).

In an attempt to maximise utility, a household in one particular sub-market, will therefore have a propensity to demand a house in a related housing sub-market that has the attributes to meet the needs arising from the characteristics of that household (Galster, 1996). In other words, as housing attributes are valued differently depending on the characteristics of households, household characteristics will influence dwelling type choice. Hence, housing sub-markets arise as a result of the way in which segmented demand is matched to the disaggregated housing stock (Watkins 2001). Consequently, by segmenting and disaggregating current households and dwelling types, it is possible to describe how households with certain characteristics may demand particular dwelling types.

A key objective of housing submarket analysis is therefore to identify unmet demand, which requires an understanding of the propensity of various households to demand particular types of housing. Data for most market segmentation studies is sourced either from the census or through market surveys, although both are susceptible to being compromised by misunderstandings, ignorance and irresponsiveness of the housing consumers (Islam & Asami, 2009).

While consumer surveys are able to capture forward-looking aspirations of households to demand a particular housing type, census data only offers a snapshot of current housing use as a proxy for demand. This creates a distortion in that current housing choices are constrained by existing stock; so historical housing propensities are not necessarily an effective predictor of future housing propensities. Furthermore, most studies tend to deal with current numbers of households and household characteristics, rather than taking into consideration future household growth and change in household composition. As a result, attempts should be made to apply propensities to future population projections to determine what types of dwellings are likely to be demanded in the future.

For the purposes of this paper, disaggregation is defined as the process of dividing the total housing stock into submarkets, within which housing units have certain characteristics (e.g. type, value, location, size or other features), which enable them to be substitutes for each other (supply-side). Whereas segmentation is defined as the process of dividing the total population of households into submarkets, within which households have certain characteristics (e.g. income, age of household head or household size), which generate similar preferences and levels of demand for certain products (demand-side) (Carn, 1988). Interestingly, drawing on the work of Lancaster (1966) and Tobin (1959), Quigley (1976) found that location, house type and tenure were the key attributes that influenced housing choice and that these influences differed depending on the age, income and family size of the household.

The following section outlines the process where the housing market is segmented and disaggregated based on individual attributes (such as age, size, income and type) respectively.

5. Segmentation & disaggregation based on single attributes – Steps 2 & 3

There are a number of widely adopted approaches to defining housing submarkets, namely structural, spatial, affordability and a combination thereof (Hogarth, 2015).

The structural approach uses house type characteristics to define housing submarkets. Payment for housing implies payment for a range of qualitative and quantitative attributes of residential structures (Quigley 1976). Definitions of submarkets along structural lines often tend to focus on dwelling types (e.g. apartment, townhouse, semi-detached or free standing) and tenure (e.g. ownership or rental). It is possible to determine dwelling type propensities by using census data or surveys to ascertain the type of housing units households would choose based on household characteristics, such as income, household size, life stage, etc. Similarly, it is possible to match household characteristics to tenure status to determine tenure propensities.

Housing markets may be disaggregated both spatially and structurally, as both spatial and structural factors give rise to submarkets – this is sometimes referred to as the hybrid-housing submarket. Grisby et al (1987 in Islam & Asami 2009) argues that housing submarkets are collections of housing units offering similar packages of housing services, where the services themselves are functionally related to the structure, as well as the characteristics of the surrounding environment and local accessibility to various amenities.

Secondly, housing markets are often disaggregated in terms of location, usually at a neighbourhood level[1] (Bourassa et al 1999).

Lastly, sub-markets are defined in terms of affordability, and households and houses are categorised in terms of income and price (Ball and Kirwan, 1977).

Hogarth (2014) and Lendor *et al* (2015) segmented and disaggregated the Cape Town market using census data, as described above. Selected results[2] from these exercises are shown in appendix 1. Due to the categorical nature and large size of the data, a Cramer's V Statistic was used to determine if there was any significant relationship between the house type chosen and the household attribute. The table 1 below suggests that household size has most influence on house type choice.

Table 1: Cramer's V Statistic result (Lendor et al, 2015)

Household Characteristic	df	Cramer's V Statistic	Effect Size
Gender of Household Head	1	0.08	Small Effect
Age of Household Head	2	0.24	Medium Effect
Household Size	2	0.39	Large Effect
Household Income	2	0.24	Medium Effect
Race of Household Head	3	0.29	Medium Effect

The above segmentation and disaggregation process can be used firstly, to assess the gap in current market and secondly, to estimate future demand for different house types.

6. Analyse the results – Step 4

6.1 Calculating the current gap in the market

The gap in current supply of housing versus the effective demand for housing can be calculated as follows (McClure, 2005). First, the number of households in each income range is identified. Then, based on an income to mortgage repayment ratio,

[1] For example, the CityMark Dashboard for South African metros (CAHF 2015).
[2] Only the propensity for single residential and flats by household attribute was shown. The research also included other housing types such as townhouses.

the value of house that can be afforded per income bracket is calculated. This is then compared to the current supply of housing by value category to calculate the excess or surplus that exists. This methodology is illustrated in figure 1 and the results for Cape Town presented in table 2.

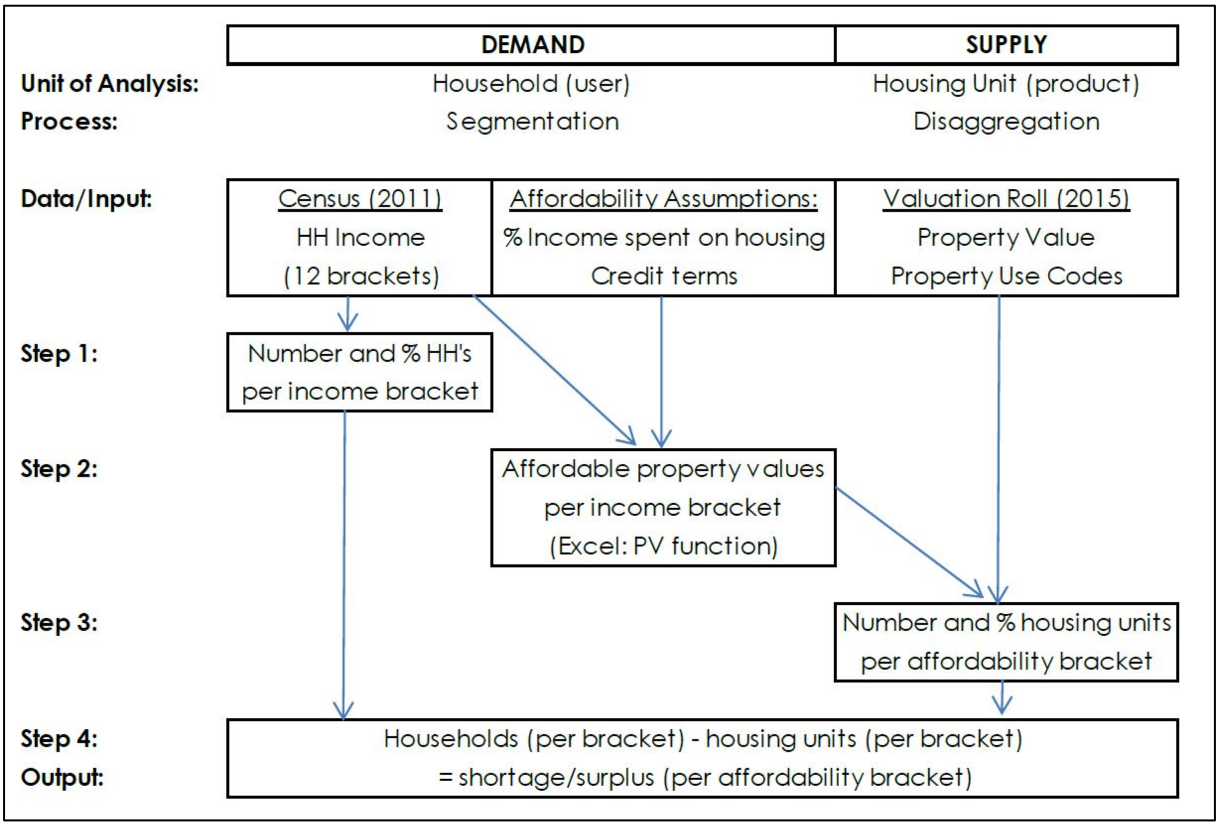

Figure 1: Gap analysis method (Hogarth, 2015)

Table 2: Gap analysis results (Hogarth, 2015)

Demand: Households					Supply: Residential Properties					Shortage/Surplus[1]	
Income Category			No. Households	% of Total	Value Category			No. Properties	% of Total	No. Properties	% of Total Stock
R 0			146 517	13.71%			R 0	0	0.00%	-146 517	-22.02%
R 1	to	R 400	29 373	2.75%	R 1	to	R 11 514	0	0.00%	-29 373	-4.41%
R 401	to	R 800	42 418	3.97%	R 11 515	to	R 23 028	0	0.00%	-42 418	-6.37%
R 801	to	R 1 600	113 277	10.60%	R 23 029	to	R 46 055	0	0.00%	-113 277	-17.02%
R 1 601	to	R 3 200	170 824	15.99%	R 46 056	to	R 92 111	48 354	7.27%	-122 470	-18.40%
R 3 201	to	R 6 400	154 427	14.45%	R 92 112	to	R 184 222	52 021	7.82%	-102 406	-15.39%
R 6 401	to	R 12 800	139 348	13.04%	R 184 223	to	R 368 443	131 106	19.70%	-8 242	-1.24%
R 12 801	to	R 25 600	126 625	11.85%	R 368 444	to	R 736 886	172 874	25.98%	46 249	6.95%
R 25 601	to	R 51 200	92 860	8.69%	R 736 887	to	R 1 473 772	160 284	24.08%	67 424	10.13%
R 51 201	to	R 102 400	38 018	3.56%	R 1 473 773	to	R 2 947 545	70 919	10.66%	32 901	4.94%
R 102 401	to	R 204 800	9 748	0.91%	R 2 947 546	to	R 5 895 089	22 880	3.44%	13 132	1.97%
R 204 801	and up		5 066	0.47%	R 5 895 090	and up		7 075	1.06%	2 009	0.30%
TOTAL			**1 068 501**	**99.99%**				**665 513**	**100.00%**	**-402 988**	**-60.55%**

6.2 Determining the future demand for different housing types

The current propensity to demand particular types of housing can be used to estimate future demand if future demographic profiles have been projected. To do this, future population figures are converted into number of households using headship calculations.

The headship rate method assumes that the number of people who head a household is equal to the number of households (Carliner, 2003). Census data from the two most recent years are used to project headship rates (Carliner, 2003). Headship rates are usually calculated based on age to match the population projection descriptions. The headships can be calculated as follows (Carliner, 2003):

$$Yi = Y1i \ x \ [(Y2i - K)/(Y1i - K)]^{\frac{Y-Y1}{Y2-Y1}}$$

Where:

Yi = projected Headship rate

Y = year of projected Headship rate

Y1 = 2001

Y2 = 2011

Y1i = 2001 Headship rate

Y2i = 2011 headship rate

K = 0 if Headship rate decreased over the period, 1 if Headship rate increased over the period. Table 3 and 4 shows the result of the headship calculation for Cape Town based on the 2001 and 2011 census.

Table 3: Propensities by age and dwelling type (Lendor et al, 2015)

PROPENSITIES BY AGE GROUP AND DWELLING TYPE					
	Single - detached	Flat or apartment	Town/cluster/semi-detached house	Informal dwelling	Total
2011					
0 to 14	477	91	102	143	813
15 to 64	517626	90992	84072	215420	908110
65+	83826	15078	18751	3211	120866
	601929	106161	102925	218774	1029789
2001					
0 to 14	72	13	6	30	121
15 to 65	389246	61795	44148	139856	635045
65+	56094	13313	9047	3081	81535
	445412	75121	53201	142967	716701

Table 4: Headship calculation for Cape Town (Lendor et al, 2015)

HEADSHIP RATES								
Age Group	**Y2i - 2011**	**Y1i - 2001**	**K**	**Y1i - K**	**Y2i - K**	**(Y2i – K)/ (Y1i – K)**	**(Y-Y1)/ (Y2-Y1)**	**Yi - 2040**
0 to 14	0,00079	0,00017	1,00	-1,000	-0,999	0,9994	3,9	0,0002
15 to 64	0,88184	0,88607	0,00	0,886	0,882	0,9952	3,9	0,8697
65+	0,11737	0,11376	1,00	-0,886	-0,883	0,9959	3,9	0,1120
	100%	100%						98,18%

Applying these headship rates to the projected population figures one can calculate the estimated number of future households as shown in table 5.

Table 5: Estimated number of future households (Lendor et al, 2015)

NUMBER OF HOUSEHOLDS IN 2040			
Age Group	2040 Population	Headship Rate	Number of Households (2040)
0 to 14	972724	0,02%	164
15 to 65	3185671	86,97%	2770575
65+	518163	11,20%	58019
			2828757

However, table 6 below shows that the propensity to demand different house types may change over time and therefore the above estimations may be adjusted to take these trends into account.

Table 6: % change in % demand per dwelling type (Lendor et al, 2015)

DWELLING TYPE PROPENSITIES					
	Single - detached	Flat or apartment	Town/cluster/semi-detached house	Informal dwelling	Total
2011	601929	106161	102925	218774	1029789
2001	445412	75121	53201	142967	716701
2011	58,45%	10,31%	9,99%	21,24%	100%
2001	62,15%	10,48%	7,42%	19,95%	100%
	-5,95%	**-1,65%**	**34,65%**	**6,50%**	
	Percentage change in proportion				

Whilst illuminating in their own right, the above segmentation and disaggregation exercises have a number of shortcomings. Firstly, they tend to be a-spatial and secondly, they determine the propensity of demand on a one-to-one relationship of predictor variable to response – in other words, only one household characteristic is used to determine demand for a particular housing type. This is arguably rather simplistic as, in reality, demand is driven by a combination of household characteristics. Therefore, a many-to-one relationship of predictor variables (household characteristics) to response (housing type) that is spatially referenced would yield a more accurate segmentation of the housing market into submarkets. The following section outlines two possible ways that this can be undertaken.

7. Segment & disaggregate the market based on multiple attributes – Step 5

7.1 Clustering approach

To determine what combination of household characteristics determines the propensity of households to demand certain house types, households need to be grouped into categories with similar characteristics. There are various statistical models for clustering that have different advantages and disadvantages and some are better suited to certain datasets than others. A common and simple, unsupervised learning algorithm that solves the clustering problem is the k-means algorithm. The algorithm requires that the number of clusters is specified upfront, following which the model uses an iterative process to classify a given dataset by placing each observation into one of the clusters. An interesting example of this application is "Whereabouts London" (Whereaboutslondon.org), which used 235 datasets to group London's households into eight clusters. Examples of the output of this exercise are shown in figures 2 and 3.

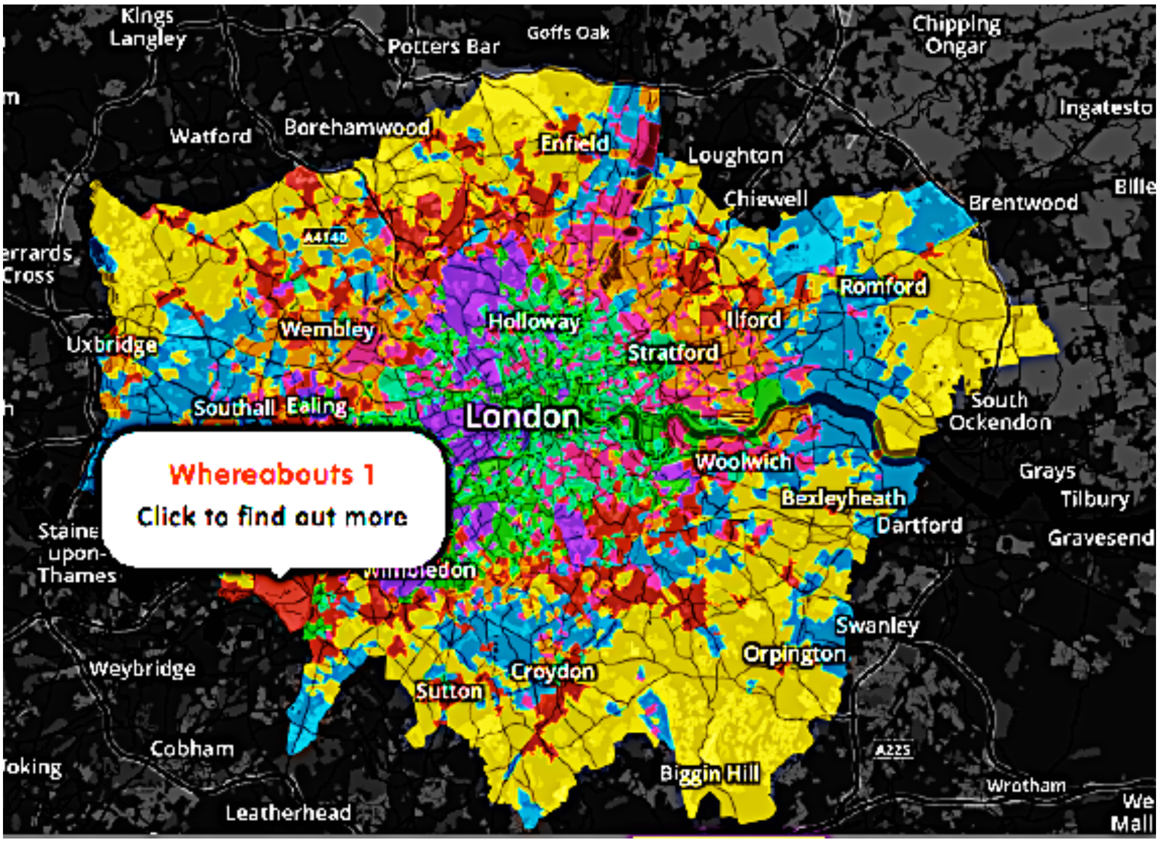

Figure 2: Whereabouts London (WhereaboutsLondon.org)

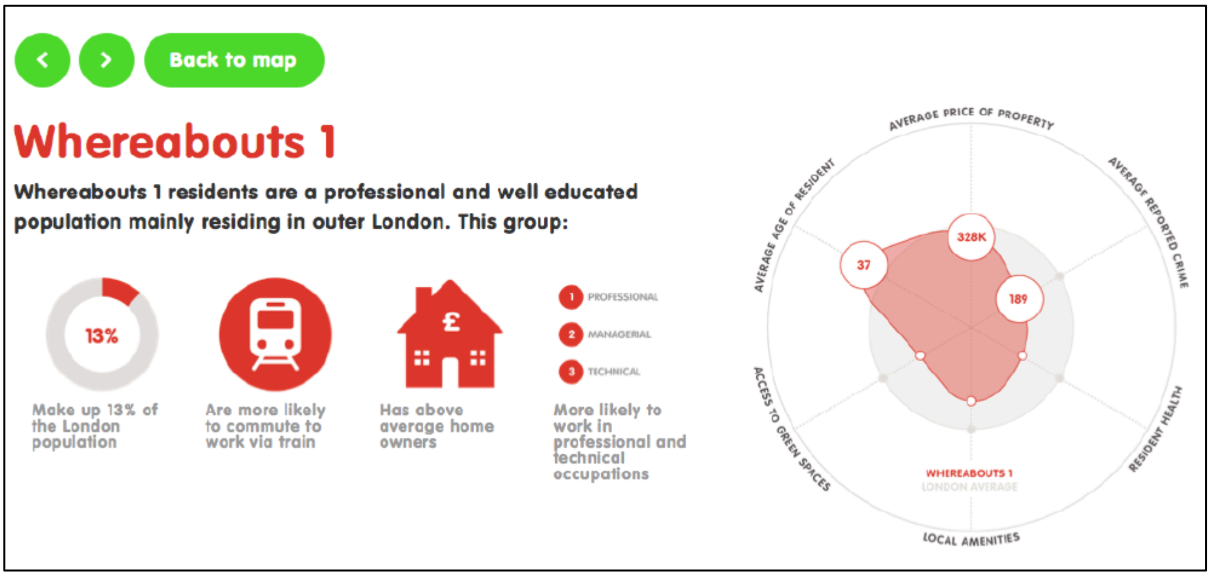

Figure 3: Whereabouts London Summary 1

This approach was used to create clusters for Cape Town using 2011 Census data. The households in Cape Town were grouped into eight categories according to household size, age, income, gender, tenure and levels of overcrowding. These clusters where then geographically located and analysed as shown in figure 4.

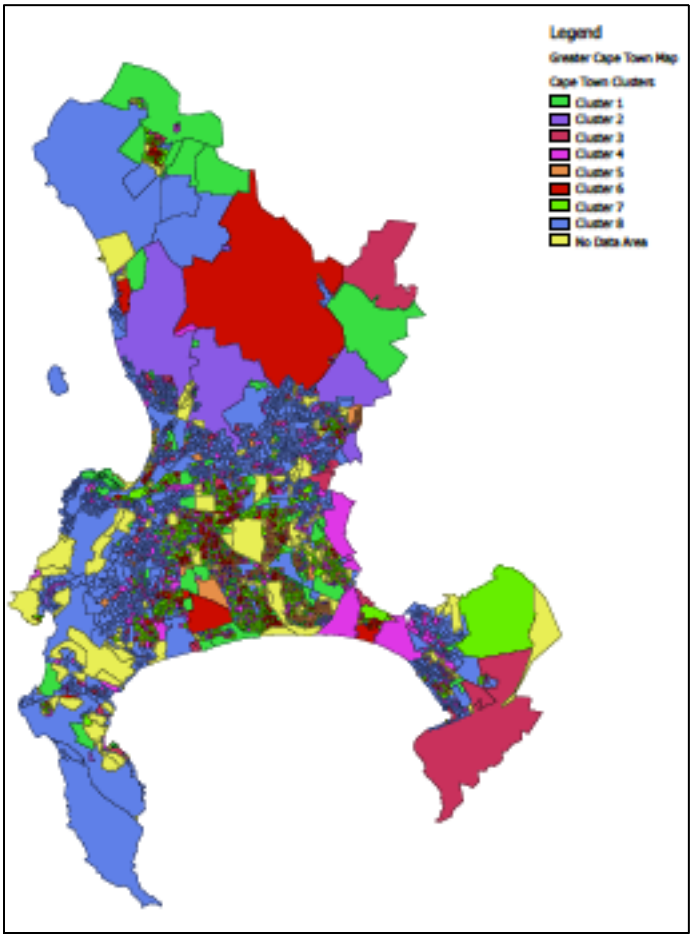

Figure 4: Whereabouts Cape Town (Lendor et al, 2015)

For example, cluster 6 contained the following type of households (Day, Kerswill, Meier Mattern, Williams-Jones, 2016):

Sub-Market 6 (e.g. Tafelsig, Mitchell's Plain, Manenberg):

- Annual Income: R38 401 to R76 800
- Dominant Age Group: 45-54
- Dominant Household Size: 4
- Dominant Housing Type: brick/concrete block house

7.2 Supervised tree decision approach[3]

The problem with using the clustering approach to determine the propensity of demand is that the population is iteratively grouped around means until logical clusters are produced. From this, one has to interrogate each cluster to determine what is common to each cluster. In another words, although associations are determined, these associations may have nothing to do with household choice – common categories may be created but these categories may have no relevance with respect to how households choose houses. As a result, a supervised learning model is a more appropriate method as the households are grouped based on their housing choice (the response).

The categorical nature of the response variable suggests that the predictive model should be of the classification type. Given that the predictor variables (household characteristics) would include both numeric and categorical variables, multi-class tree based methods would be the most suitable for learning a predictive model. Although multi-class logistic regression could also work, tree based methods stand out in terms of performance especially if the underlying decision boundaries in the data are non-linear.

Tree based methods are based on decision trees. These are a non-parametric supervised learning models meaning they support data with varied distributions of responses. The goal is to “learn a model” that predicts the value of a target variable by learning simple decision rules inferred from the data features. In each tree, a sequence of simple tests are run for each class, increasing the levels of a tree structure until a leaf node (decision) is reached. For multi-class problems, tree based methods work well by building multiple decision trees known as random forests. To predict the class of a new object from an input vector, the input vector is fed into each of the trees in the forest. Each tree gives a classification, a "vote" for that class. The classification having the most votes over all the trees in the forest is then chosen. The trees that have high prediction confidence will have a greater weight in the final decision of the ensemble.

Decision trees use an algorithm in the selection of the variable to split on at a node. The algorithm splits the nodes on all available variables and then selects the split that results in the most homogeneous sub-nodes. There are four commonly used algorithms in decision trees: Gini index, Chi-square, Information gain and Variance.

[3] This section draws heavily from documentation provided by Mr. Jawu Nyirenda and Ms. Reshma Kassanjee from the UCT Department of Statistical Sciences. In some cases, their work has been directly reproduced.

The first three are used when the response variable is categorical whilst the fourth is used when the response is continuous as in regression trees.

Put more simply, a predictor variable such as age would be chosen and all households above and below certain age categories would be grouped into different branches. Then another predictor variable such as income would be applied to each branch and a new set of branches based on income thresholds would be created under each branch. Once all the variables have been applied, the dominant house type is identified for each branch string. The process is designed such that each branch string will result in a dominant house type being identified.

Some of the advantages of tree-based methods such as random forests include the following:

- Requires little data preparation.
- Efficient in computation and memory usage during training and prediction.
- Able to handle both numerical and categorical data.
- Able to handle multi-class problems.
- High accuracy, stability and ease of interpretation.
- Do not over-fit.
- Simultaneously performs predictor selection and classification.
- Performs well even with noisy data.

The other technique available for learning a predictive model is the Support Vector Machine (SVM). This is an optimising technique and can achieve extremely high levels of accuracy. Through the use of the kernel function, the technique can handle data with non-linear decision boundaries too; however, SVM's can be computationally expensive.

8. Conclusion

The purpose of this paper was to demonstrate the importance of developing a nuanced understating of market demand and market segmentation in order to better inform the actions of both the public and private sector with regards to housing, and to make suggestions as to a possible methodology for segmenting the housing market into appropriate submarkets. The paper showed how the market could be divided into sub-markets using structural and affordability approaches based on single household attributes. From this, the gap between supply and demand was determined and future house types demands estimated. Following this, multi-variable segmentation techniques were discussed, with a supervised learning tree-based model chosen as the preferred technique. This is because it offers certain advantages when working with both numeric and categorical data and with data that has varied distributions of responses, as is the case with census household data. It is recommended that this model be applied to Cape Town census data in order to provide findings that could lead to more informed market and policy responses to the current housing problem.

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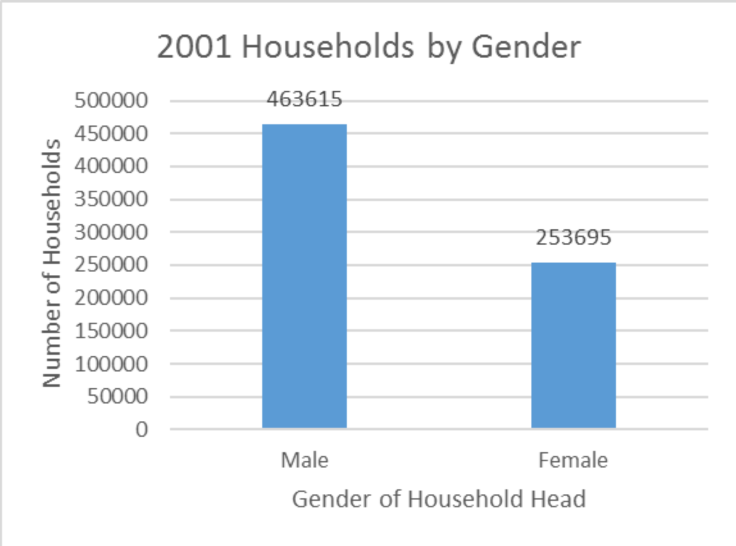
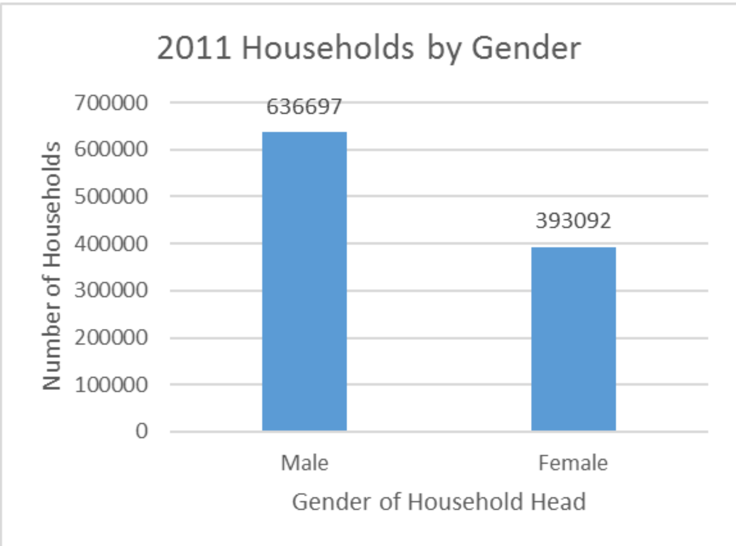
Appendix 1

Structural segmentation of the Cape Town market:

Gender:





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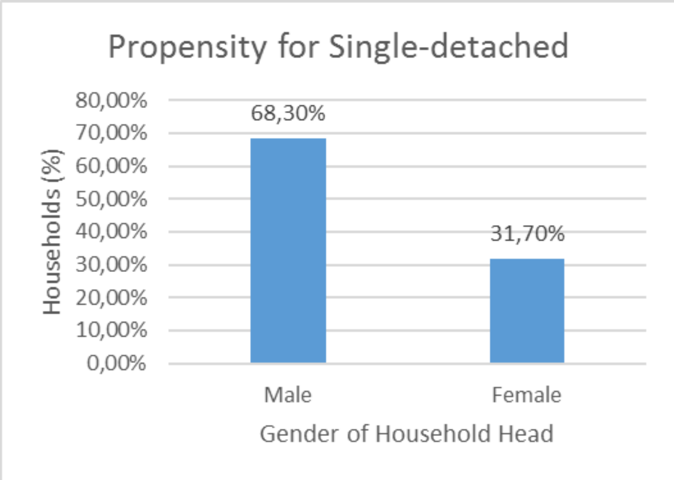
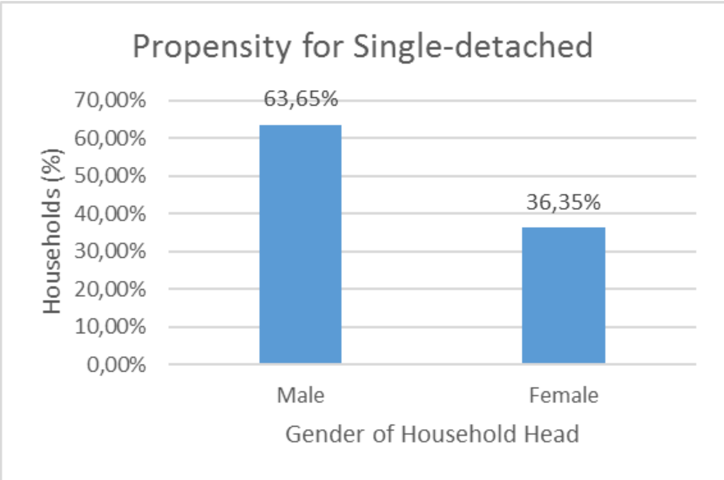
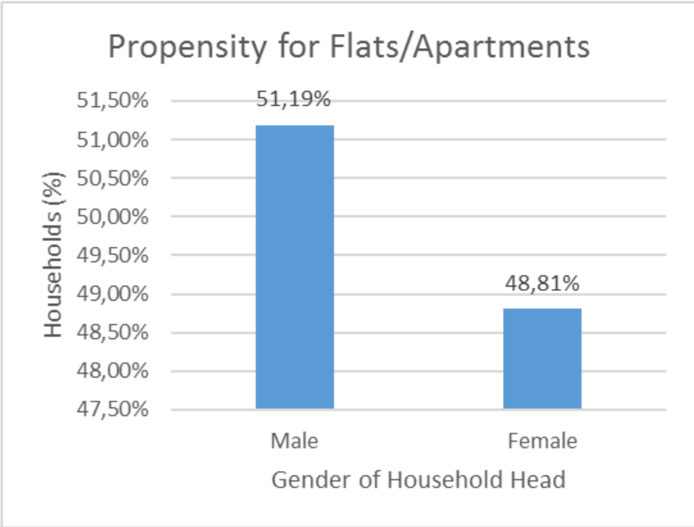

Propensity for Single-detached
80,00%
70,00%
60,00%
50,00%
40,00%
30,00%
20,00%
10,00%
0,00%
Households (%)
68,30%
31,70%
Male
Female
Gender of Household Head

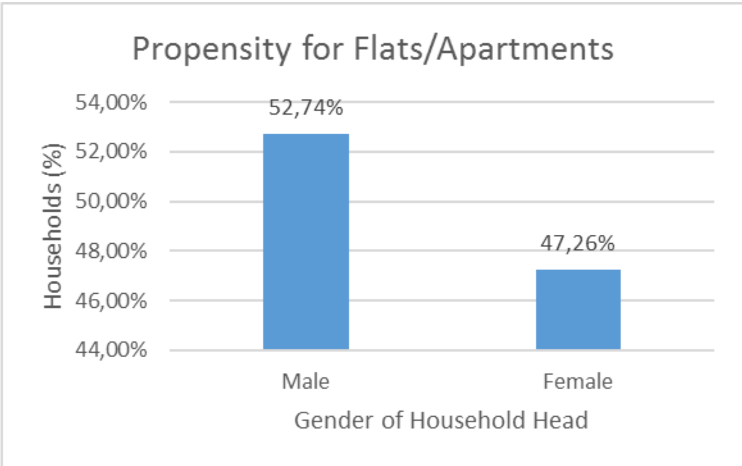
2011:


Propensity for Single-detached
70,00%
60,00%
50,00%
40,00%
30,00%
20,00%
10,00%
0,00%
Households (%)
63,65%
36,35%
Male
Female
Gender of Household Head

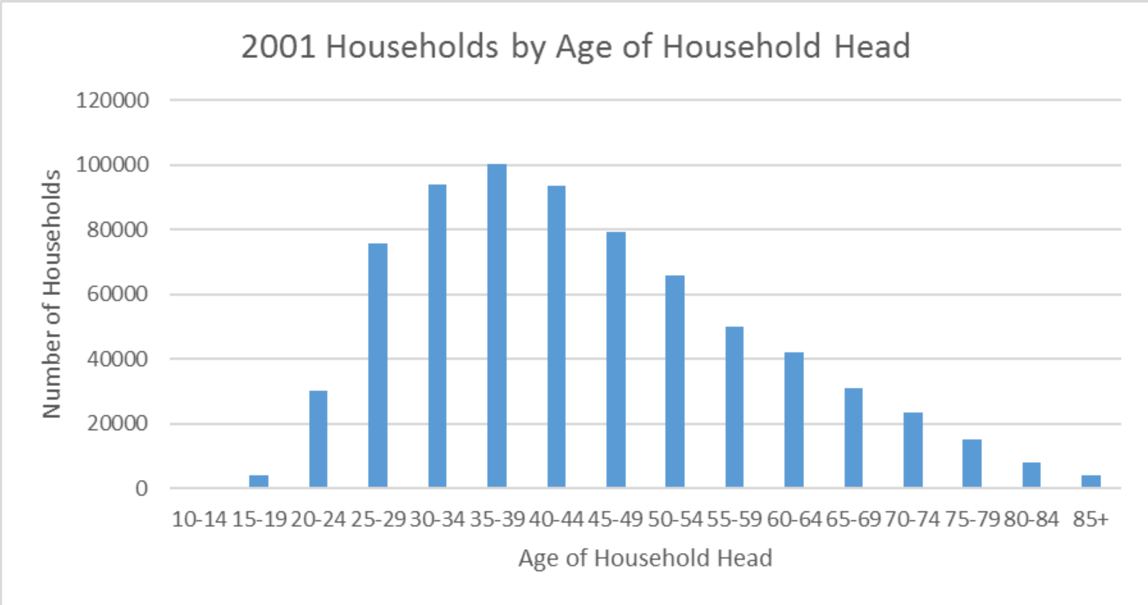
2001:

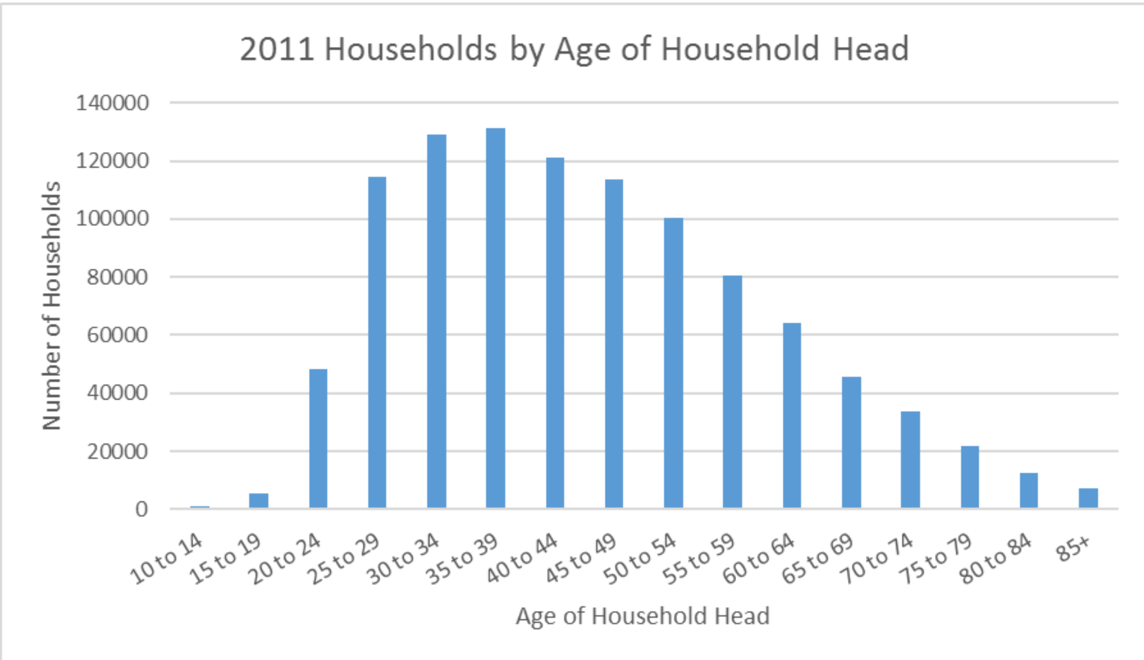

Propensity for Flats/Apartments
Households (%)
51,50%
51,00%
50,50%
50,00%
49,50%
49,00%
48,50%
48,00%
47,50%
51,19%
48,81%
Male
Female
Gender of Household Head

2011:

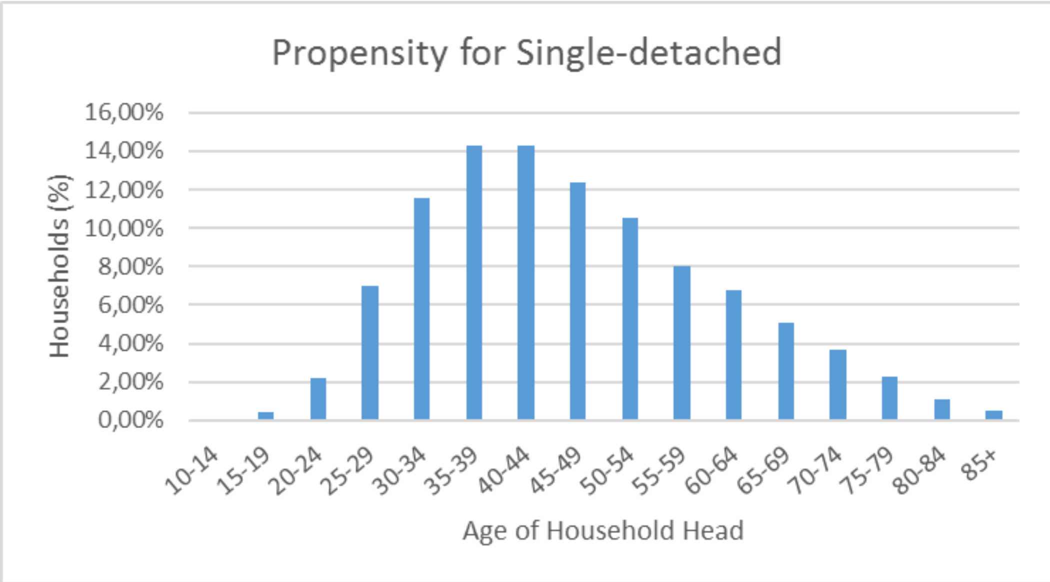

Propensity for Flats/Apartments
Households (%)
54,00%
52,00%
50,00%
48,00%
46,00%
44,00%
52,74%
47,26%
Male
Female
Gender of Household Head

Age:

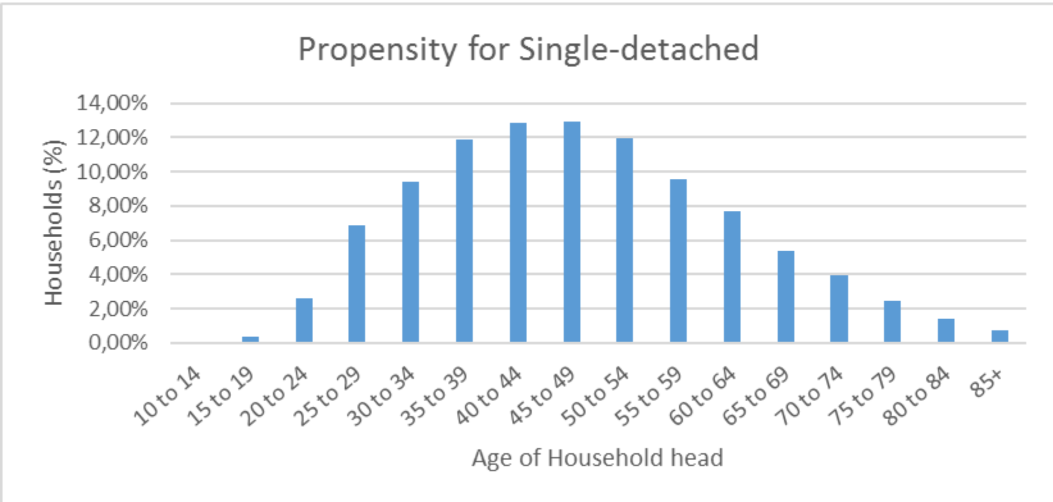

2001 Households by Age of Household Head
Number of Households
120000
100000
80000
60000
40000
20000
0
10-14 15-19 20-24 25-29 30-34 35-39 40-44 45-49 50-54 55-59 60-64 65-69 70-74 75-79 80-84 85+
Age of Household Head


2011 Households by Age of Household Head
Number of Households
140000
120000
100000
80000
60000
40000
20000
0
10 to 14 15 to 19 20 to 24 25 to 29 30 to 34 35 to 39 40 to 44 45 to 49 50 to 54 55 to 59 60 to 64 65 to 69 70 to 74 75 to 79 80 to 84 85+
Age of Household Head

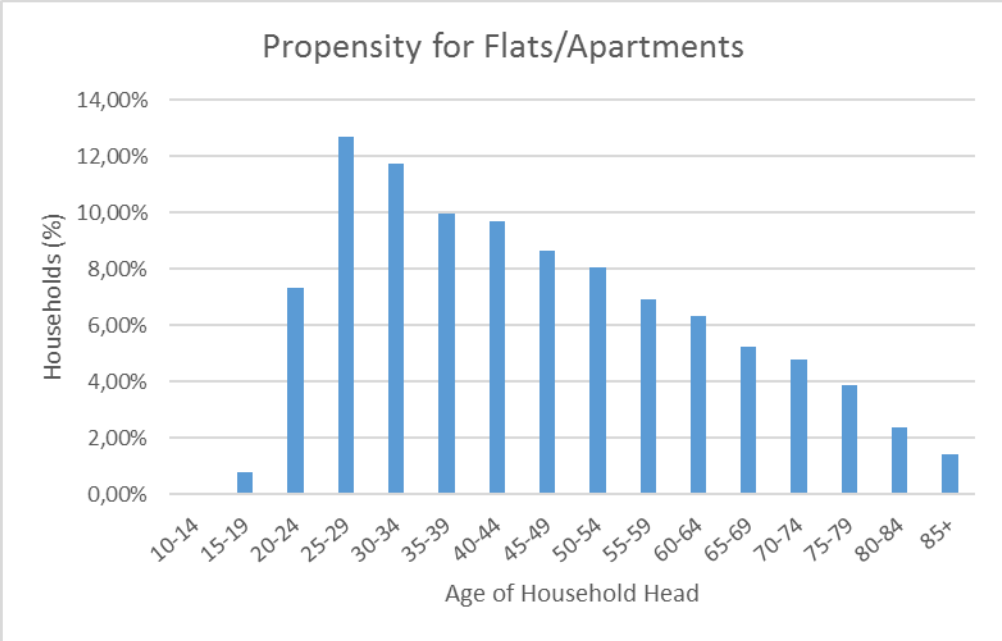
2001:


Propensity for Single-detached
16,00%
14,00%
12,00%
10,00%
8,00%
6,00%
4,00%
2,00%
0,00%
Households (%)
10-14
15-19
20-24
25-29
30-34
35-39
40-44
45-49
50-54
55-59
60-64
65-69
70-74
75-79
80-84
85+
Age of Household Head

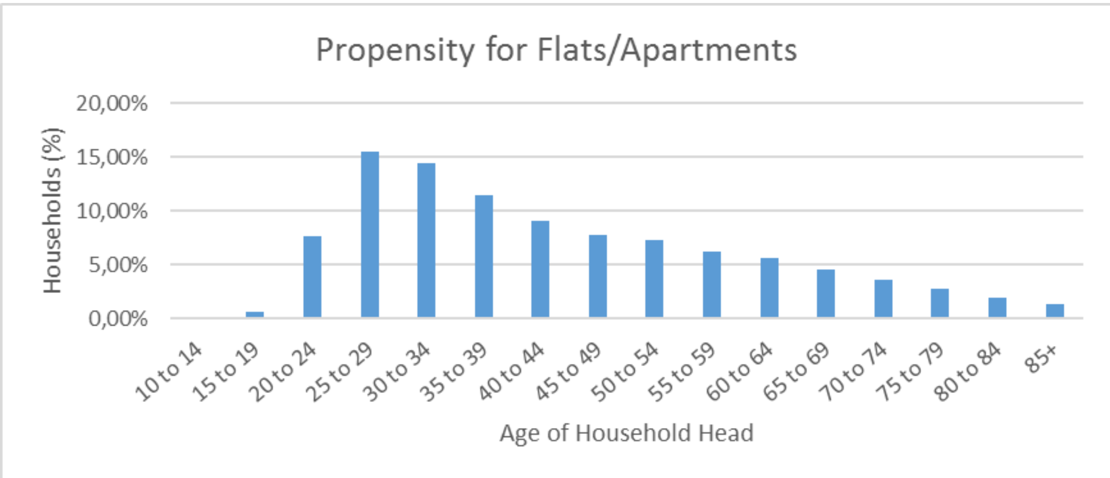
2011:


Propensity for Single-detached
14,00%
12,00%
10,00%
8,00%
6,00%
4,00%
2,00%
0,00%
Households (%)
10 to 14
15 to 19
20 to 24
25 to 29
30 to 34
35 to 39
40 to 44
45 to 49
50 to 54
55 to 59
60 to 64
65 to 69
70 to 74
75 to 79
80 to 84
85+
Age of Household head

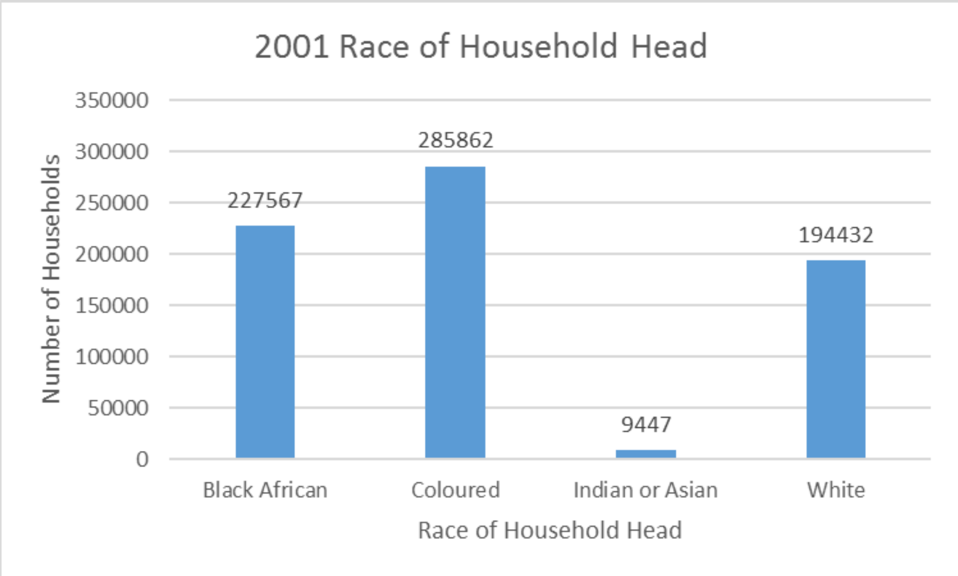
2001:

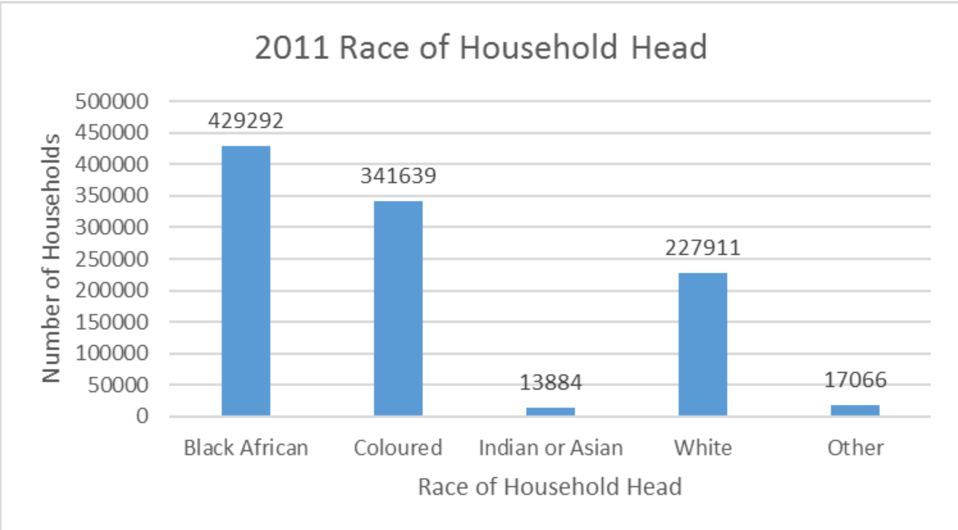

Propensity for Flats/Apartments
Households (%)
14,00%
12,00%
10,00%
8,00%
6,00%
4,00%
2,00%
0,00%
10-14
15-19
20-24
25-29
30-34
35-39
40-44
45-49
50-54
55-59
60-64
65-69
70-74
75-79
80-84
85+
Age of Household Head

2011:

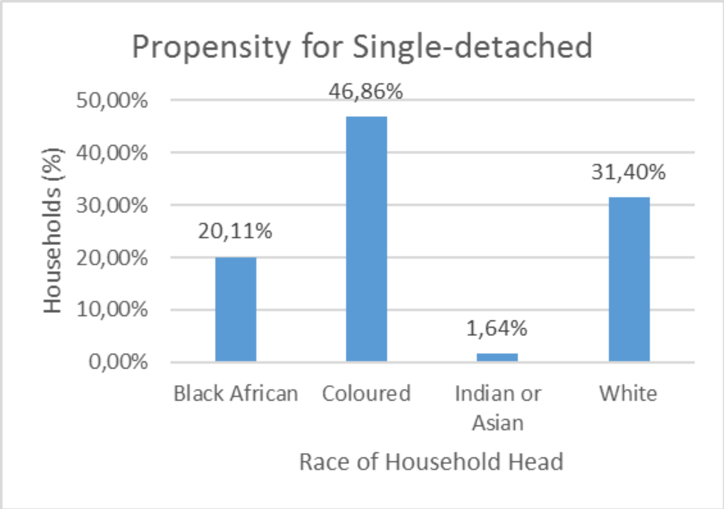

Propensity for Flats/Apartments
Households (%)
20,00%
15,00%
10,00%
5,00%
0,00%
10 to 14
15 to 19
20 to 24
25 to 29
30 to 34
35 to 39
40 to 44
45 to 49
50 to 54
55 to 59
60 to 64
65 to 69
70 to 74
75 to 79
80 to 84
85+
Age of Household Head

Race:

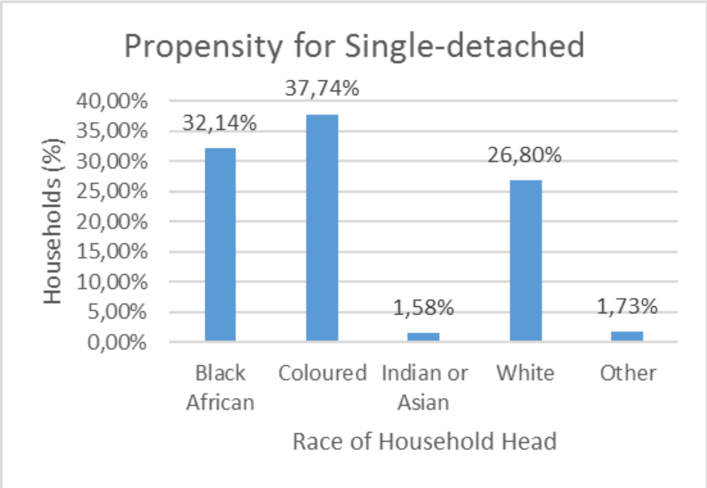

2001 Race of Household Head
Number of Households
350000
300000
250000
200000
150000
100000
50000
0
227567
285862
9447
194432
Black African
Coloured
Indian or Asian
White
Race of Household Head


2011 Race of Household Head
Number of Households
500000
450000
400000
350000
300000
250000
200000
150000
100000
50000
0
429292
341639
13884
227911
17066
Black African
Coloured
Indian or Asian
White
Other
Race of Household Head

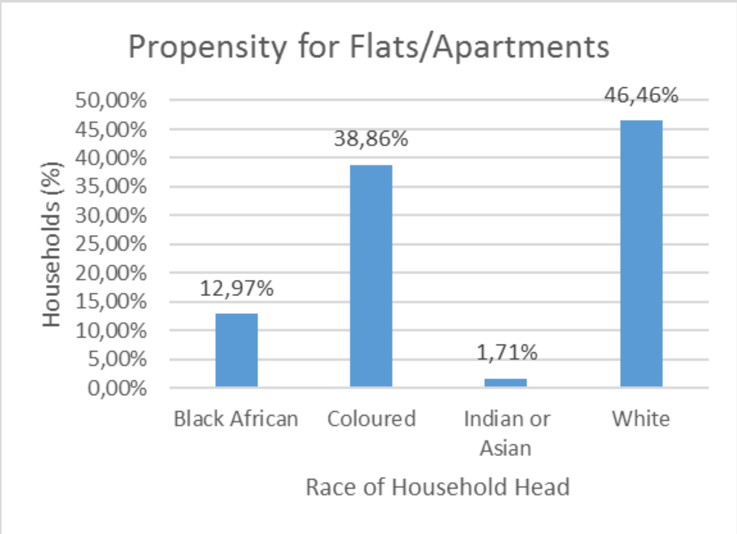
2001:


Propensity for Single-detached
Households (%)
50,00%
40,00%
30,00%
20,00%
10,00%
0,00%
20,11%
46,86%
1,64%
31,40%
Black African
Coloured
Indian or Asian
White
Race of Household Head

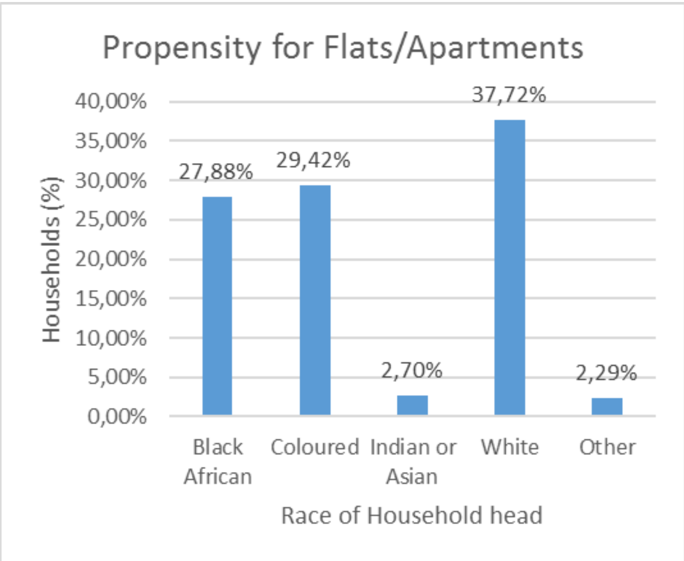
2011:


Propensity for Single-detached
Households (%)
40,00%
35,00%
30,00%
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
32,14%
37,74%
1,58%
26,80%
1,73%
Black African
Coloured
Indian or Asian
White
Other
Race of Household Head

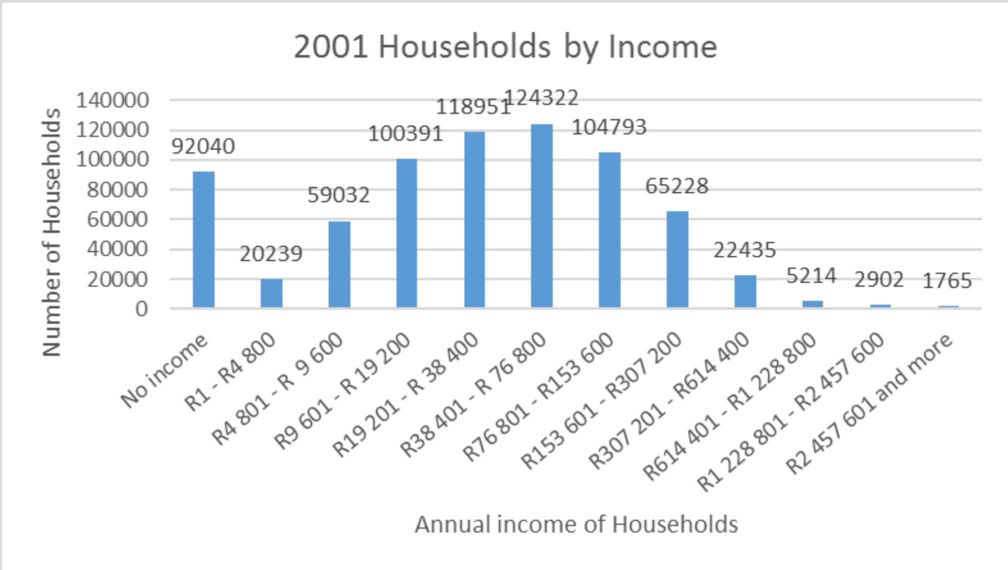
2001:

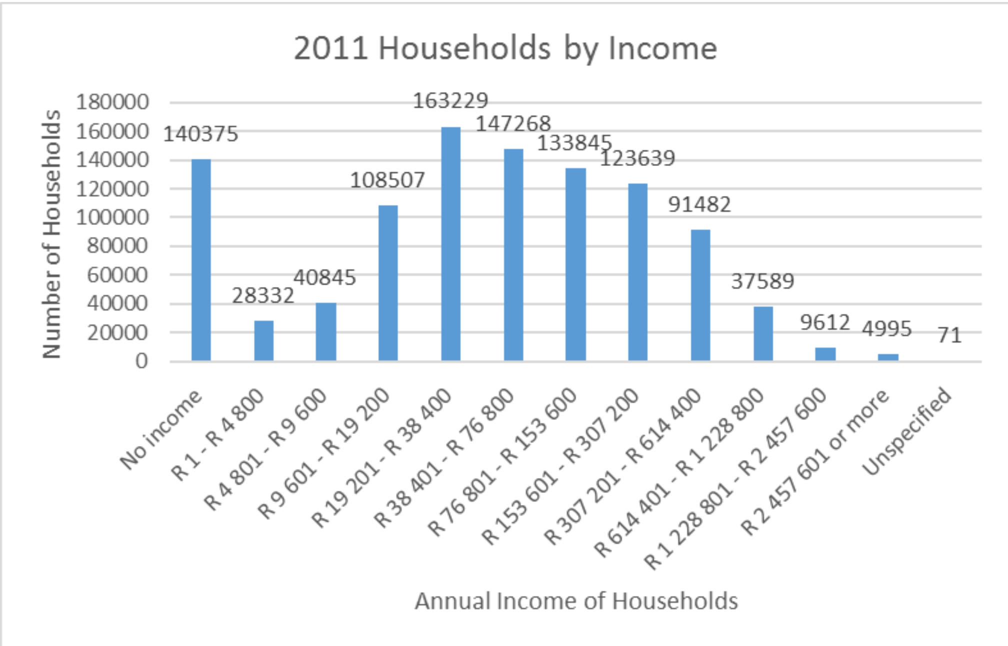

Propensity for Flats/Apartments
Households (%)
50,00%
45,00%
40,00%
35,00%
30,00%
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
12,97%
38,86%
1,71%
46,46%
Black African
Coloured
Indian or Asian
White
Race of Household Head

2011:

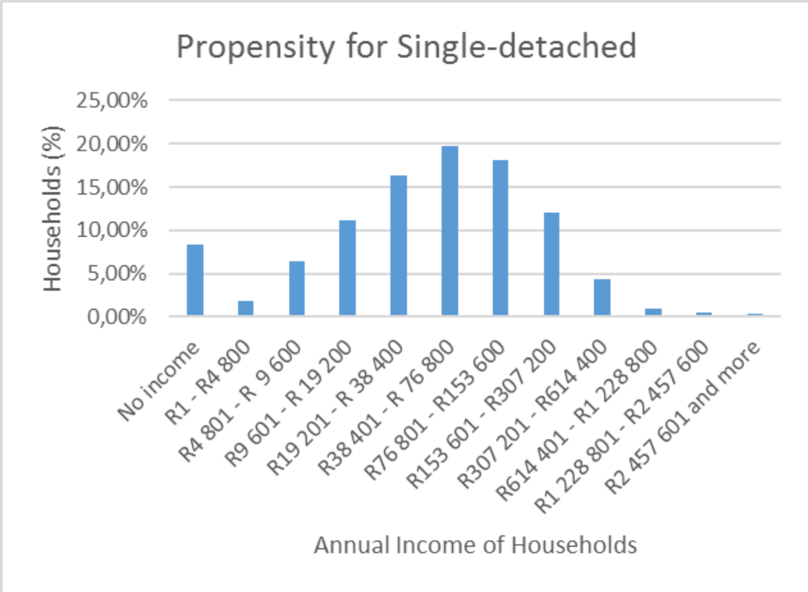

Propensity for Flats/Apartments
Households (%)
40,00%
35,00%
30,00%
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
27,88%
29,42%
2,70%
37,72%
2,29%
Black African
Coloured
Indian or Asian
White
Other
Race of Household head

Income:

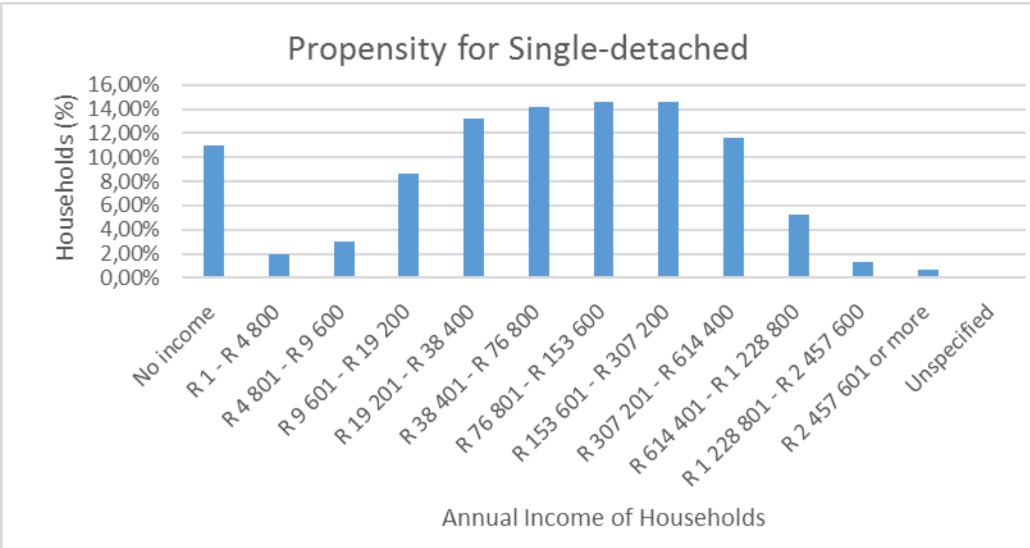

2001 Households by Income
Number of Households
140000
120000
100000
80000
60000
40000
20000
0
92040
20239
59032
100391
118951
124322
104793
65228
22435
5214
2902
1765
No income
R1 - R4 800
R4 801 - R 9 600
R9 601 - R 19 200
R19 201 - R 38 400
R38 401 - R 76 800
R76 801 - R153 600
R153 601 - R307 200
R307 201 - R614 400
R614 401 - R1 228 800
R1 228 801 - R2 457 600
R2 457 601 and more
Annual income of Households


2011 Households by Income
Number of Households
180000
160000
140000
120000
100000
80000
60000
40000
20000
0
140375
28332
40845
108507
163229
147268
133845
123639
91482
37589
9612
4995
71
No income
R 1 - R 4 800
R 4 801 - R 9 600
R 9 601 - R 19 200
R 19 201 - R 38 400
R 38 401 - R 76 800
R 76 801 - R 153 600
R 153 601 - R 307 200
R 307 201 - R 614 400
R 614 401 - R 1 228 800
R 1 228 801 - R 2 457 600
R 2 457 601 or more
Unspecified
Annual Income of Households

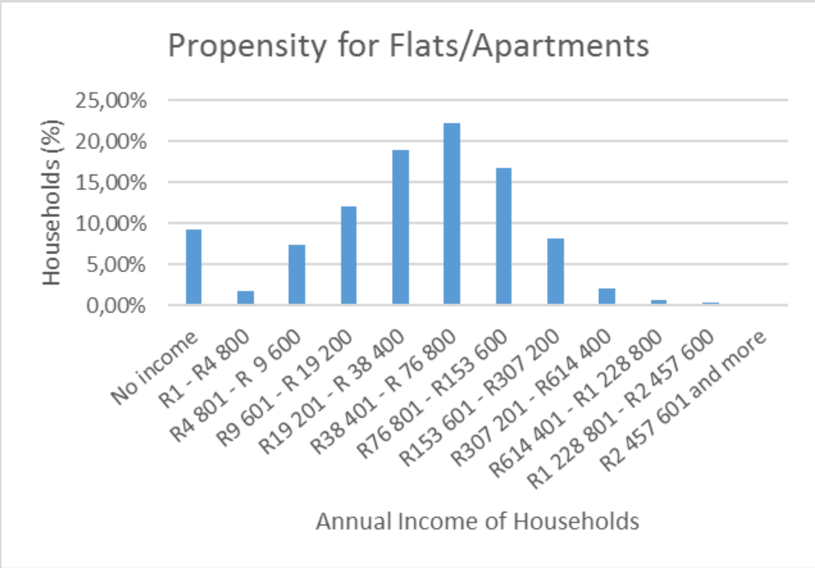
2001:


Propensity for Single-detached
Households (%)
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
No income
R1 - R4 800
R4 801 - R 9 600
R9 601 - R 19 200
R19 201 - R 38 400
R38 401 - R 76 800
R76 801 - R153 600
R153 601 - R307 200
R307 201 - R614 400
R614 401 - R1 228 800
R1 228 801 - R2 457 600
R2 457 601 and more
Annual Income of Households

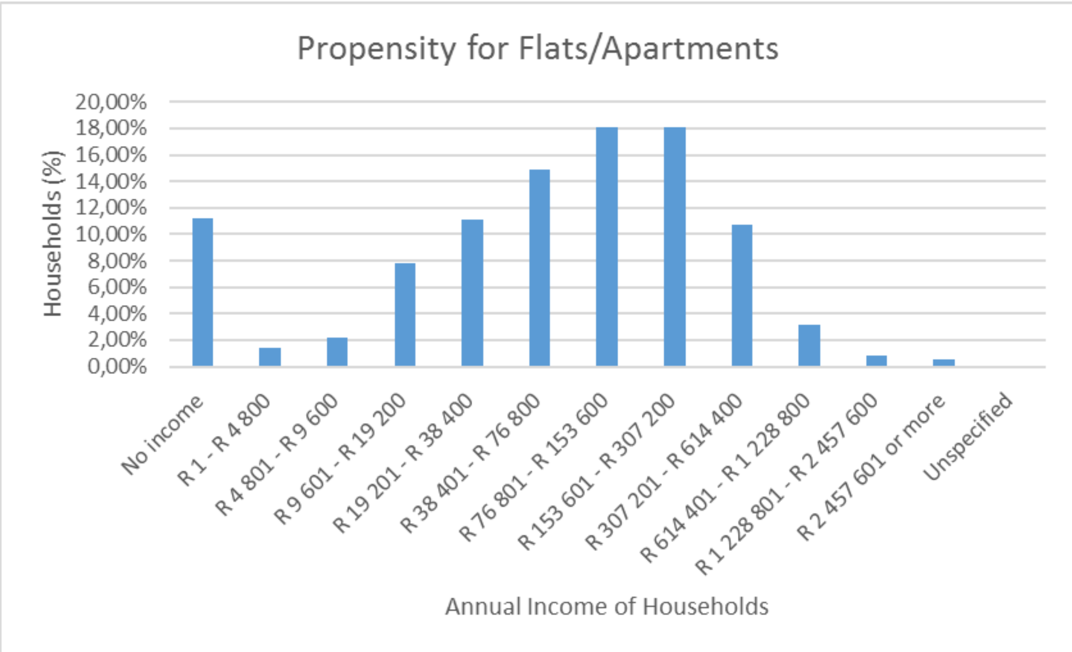
2011:


Propensity for Single-detached
Households (%)
16,00%
14,00%
12,00%
10,00%
8,00%
6,00%
4,00%
2,00%
0,00%
No income
R 1 - R 4 800
R 4 801 - R 9 600
R 9 601 - R 19 200
R 19 201 - R 38 400
R 38 401 - R 76 800
R 76 801 - R 153 600
R 153 601 - R 307 200
R 307 201 - R 614 400
R 614 401 - R 1 228 800
R 1 228 801 - R 2 457 600
R 2 457 601 or more
Unspecified
Annual Income of Households

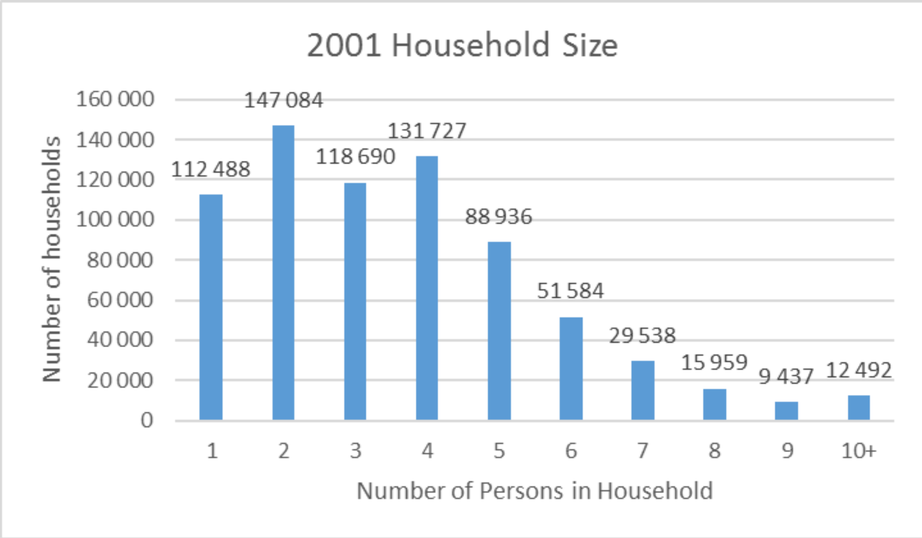
2001:


Propensity for Flats/Apartments
Households (%)
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
No income
R1 - R4 800
R4 801 - R 9 600
R9 601 - R 19 200
R19 201 - R 38 400
R38 401 - R 76 800
R76 801 - R153 600
R153 601 - R307 200
R307 201 - R614 400
R614 401 - R1 228 800
R1 228 801 - R2 457 600
R2 457 601 and more
Annual Income of Households

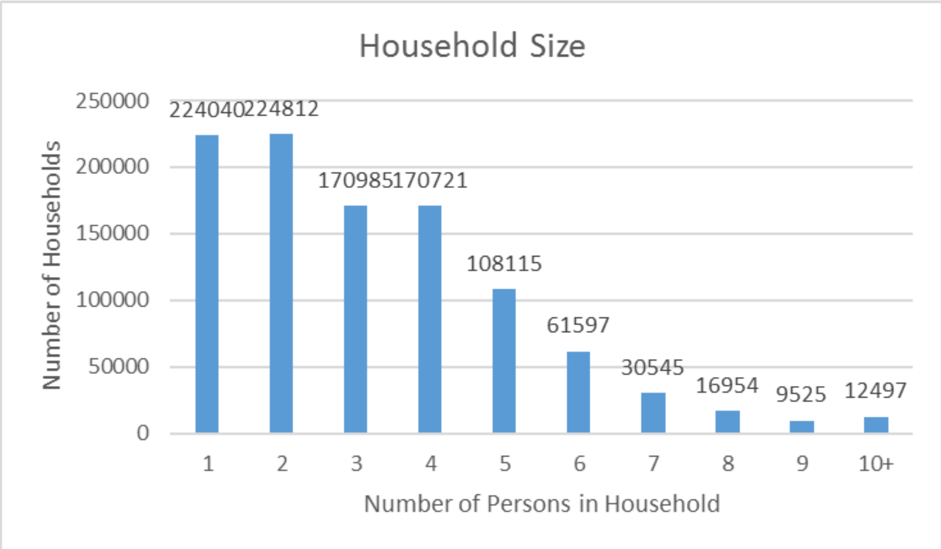
2011:


Propensity for Flats/Apartments
Households (%)
20,00%
18,00%
16,00%
14,00%
12,00%
10,00%
8,00%
6,00%
4,00%
2,00%
0,00%
No income
R 1 - R 4 800
R 4 801 - R 9 600
R 9 601 - R 19 200
R 19 201 - R 38 400
R 38 401 - R 76 800
R 76 801 - R 153 600
R 153 601 - R 307 200
R 307 201 - R 614 400
R 614 401 - R 1 228 800
R 1 228 801 - R 2 457 600
R 2 457 601 or more
Unspecified
Annual Income of Households

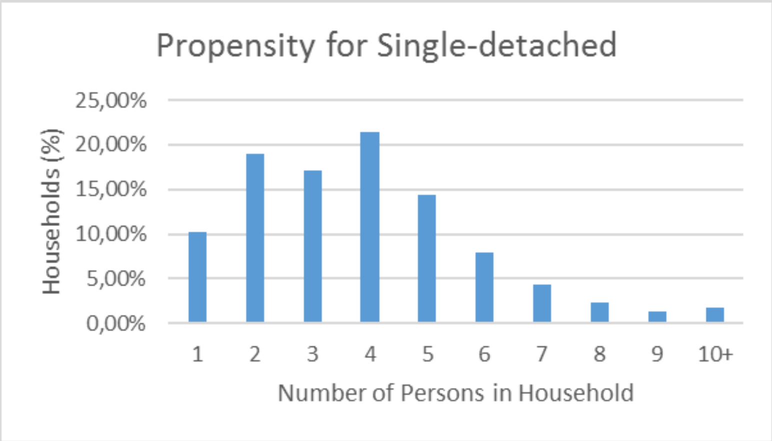
Size:


2001 Household Size
Number of households
160 000
140 000
120 000
100 000
80 000
60 000
40 000
20 000
0
112 488
147 084
118 690
131 727
88 936
51 584
29 538
15 959
9 437
12 492
1
2
3
4
5
6
7
8
9
10+
Number of Persons in Household

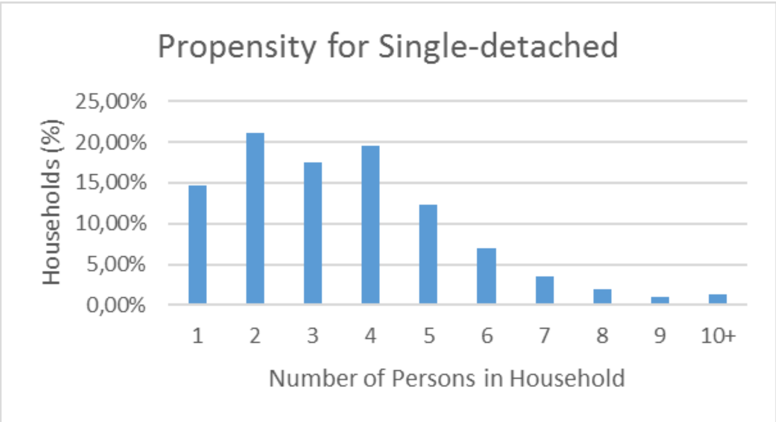
2011:


Household Size
Number of Households
250000
200000
150000
100000
50000
0
224040
224812
170985
170721
108115
61597
30545
16954
9525
12497
1
2
3
4
5
6
7
8
9
10+
Number of Persons in Household

2001:


Propensity for Single-detached
Households (%)
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
1
2
3
4
5
6
7
8
9
10+
Number of Persons in Household

2011:


Propensity for Single-detached
Households (%)
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
1
2
3
4
5
6
7
8
9
10+
Number of Persons in Household

2001:


Propensity for Flats/Apartments
Households (%)
35,00%
30,00%
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
1
2
3
4
5
6
7
8
9
10+
Number of Persons in Household

2011:


Propensity for Flats/Apartments
Households (%)
40,00%
35,00%
30,00%
25,00%
20,00%
15,00%
10,00%
5,00%
0,00%
1
2
3
4
5
6
7
8
9
10+
Number of Persons in Household