Comparing Consumption-based Asset Pricing Models: The Case of an Asian City

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ABSTRACT

Eight consumption-based asset pricing models are developed, estimated and compared their capacities in accounting for the asset markets in Hong Kong. Results based on conventional metrics or recently developed econometric techniques deliver similar results: introducing housing into the consumption-based models does not always improve the models' performance; how it is introduced matters. Recursive utility model and its housing-augmented variant, which emphasize the importance of early resolution of uncertainty and long term risk, outperform alternative models in forecasting stock returns. Collateral constraint model outperforms in predicting housing return, suggesting the importance of imperfect capital market in the housing market.

JEL classification: G12, E20, R30

Key words: Consumption-based asset pricing model; Recursive utility; Habit formation; Consumption growth risk; Composition risk; Labor income risk; Long-run risk; Collateral constraint; Hansen-Jagannathan distance; Model confidence sets.

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1. INTRODUCTION

This paper attempts to contribute to the literature by identifying the key determinants of the asset prices. More specifically, this paper constructs a series of consumption-based asset price models, and compares their empirical performance in explaining the housing and stock markets. As each model emphasizes a different set of driving force for the asset price movements, a comparison of model performance approximates a scientific assessment of different theories; each highlights a different set of asset price determinants. An evaluation of alternative asset price theories goes beyond intellectual curiosity. The trend of increasing integration of asset markets, the co-movements of the aggregate economy and asset markets during the recent global financial crisis may point to a different role of the central banks, as well as government intervention in the midst of potential asset market failure.[1] To address such a need, a *unifying framework* of the asset markets and the macro- economy is clearly demanded.

In fact, the economics literature has long sought to establish such a framework. For instance, Consumption-based Capital Asset Pricing Model (referred to canonical CCAPM hereafter), originally raised by Lucas (1978) and others, has been developed to relate the aggregate consumption to the stock market. Following the canonical CCAPM, researchers modified and extended the canonical model mainly in order to improve its empirical performance, including: (1) Recursive Preference (Epstein and Zin, 1989, 1991; Weil, 1989); (2) Habit Formation (Abel, 1990, 1999; Campbell and Cochrane, 1999; Constantinides, 1990). A common theme among these models is time-non-separability, i.e. they allow the marginal utility of consumption in the current period depends on previous period consumption or some valuation on the possible future holding.[2] We will provide more discussion on this in later sections.

Recently, researchers have also extended the canonical CCAPM to include housing in the utility function (as a durable consumption good) and in the budget constraint (as an asset).

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[1] It is beyond the scope of this paper to discuss this literature. Among others, see Claessens et al. (2014) and the reference therein.

[2] Among others, see also Leung and Chen (2006, 2010) on the implications of time-non-separability on the asset price movements.

Piazzesi, Schneider and Tuzel (2005) label that as "Housing CCAPM" (HCCAPM). The main idea of this model is that the representative agent not only concerns the consumption volatility, but also the composition risk: the fluctuation in the relative share of housing service in their consumption basket. They also show that the non-housing consumption share can be useful in predicting the stock return, suggesting that there is a cross-market informational spillover. Other authors introduce housing collateral constraint (among others, Lustig and Nieuwerburgh, 2005; Iacoviello, 2004), or labor income and home production (Ludvigson and Campbell, 2001; Santos and Veronesi, 2006; Davis and Martin, 2009, etc.) into the model, which seem to improve the asset price prediction.

Following all these contributions, this paper attempts to complement the literature by providing a comparison of model performance with data of an Asian city, namely, Hong Kong. [3]As most of the previous literature focus on the U.S. data, there are reasons to re-examine these models in a different context.[4] First, the United States is a large country and hence the national housing price index is inevitably a weighted average of the house prices among very different regions (for instance, see Green et al, 2005). In contrast, Hong Kong is only a small city in terms of geographical area (only about 8% of the New York City), and hence the degree of "aggregation bias" in the Hong Kong housing price index may be lower than that in the U.S. national counterpart (for instance, see Hanushek et al, 2004). At the same time such a small area has about seven million inhabitants currently. The high population density of Hong Kong also leads to the existence of an active housing market, which may facilitate the interpretation. Second, this paper can provide a robustness check, for instance, whether the results in the previous contributions depend on certain institutional setting specific to the United States. For instance, the U.S. practices local public finance in the sense that the local public goods (including the service of public education, local civil servants, etc.) are financed by the property tax in the local district, the counterpart in Hong Kong is financed by the total government revenue of the Hong Kong government, which tends to make "local sorting" less

[3] After the circulation of the first version of the paper, we are informed about the existence of Gordon and Samson (2002), which compare the canonical CCAPM, a CES-extension and the recursive utility model with Canadian data. They did not include housing in their analysis and they did not include neither the home production nor the collateral constraint model in their comparison.

[4] An important exception is Hwang and Lum (2010). More discussion on that paper will be followed.

severe in Hong Kong.[5] Third, from the perspective of economic and financial market development, Hong Kong is a typical example for the case of "intermediate" development level, in the sense that it is not as developed as the U.S. and at the same time at least as developed as most countries in Asia. Hence, there may be some lessons for other countries currently or going to have the same degree of development. Fourth, certain aspects of the institutional setting in Hong Kong may help to simplify the analysis. For instance, Hong Kong uses effectively linear tax with no capital gain while US has progressive tax with capital gain, which could potentially affect the trading behavior. During our sampling period, the nominal exchange rate between the U.S. dollar and Hong Kong dollar is fixed, with no capital control or other origin-based discriminating policies imposed in Hong Kong.[6] Moreover, due to various historical reasons, the boundary of Hong Kong has been fixed even before the Second World War.[7] All these reasons stated above make Hong Kong a natural candidate for a comparison study.

It also seems to be a natural practice to compare the performance across different models. Obviously, all models are abstract of the reality and hence no model can capture every aspect of the reality. Nevertheless, for academic as well as policy reasons, we are still interested in knowing the "important driving forces" of the asset markets, which may not be directly observable. A comparison of model performance would shed light on those driving forces. For instance, if the "collateral model" outperforms the alternatives, it may follow that the capital market imperfection is indeed a very crucial factor of the asset market. On the other hand, if the "labor income model" outperforms the others, it may suggest that the labor market exerts significant influence to the asset market.

To facilitate the comparison, therefore, we actually present both several existing models of asset pricing, plus the extensions which include housing. Thus we allow for the fact that while some models may not be able to account for the stock market as well as other competing models, the "housing-augmented version" may enhance the performance.

[5] For an analysis on how the finance of local public goods can affect the sorting of economic agents and hence affect the housing market, see Hanushek and Yilmaz (2007), among others.

[6] In contrast, some countries will give a tax-advantage to citizens versus foreigners, while some will give a tax-disadvantage.

[7] In contrast, many cities in the U.S. have been expanding in terms of geographical areas in the last few decades.

Alternatively, those "housing-augmented versions" may provide superior performance in accounting for the housing market performance. More specifically, the models that we consider for comparison can be divided into four groups: (1) the consumption-based asset pricing models including canonical CCAPM, Habit formation model and Recursive utility model; (2) the housing-augmented version of consumption-based models: Housing-CCAPM, Housing-Habit formation model and Housing-Recursive utility model; (3) the model contains labor income and home production; (4) the collateral constraint model considering borrowing capacity of indebted households.

Equipped with all these models, we are able to address the following questions: First, whether the housing-augmented versions outperform the original consumption-based models in predicting the stock return; Second, which model provides the best chance to explain both HK's stock and housing price data; Third, whether the consideration of the labor income or collateral constraint provides superior empirical performance than the alternatives.

Clearly, we are not the first attempt to study the empirical performance of consumption-based models in Asia. For instance, Hwang and Lum (2010) (henceforth HL) study a version of HCCAPM and examine its ability to account for both the stock market and the housing market in Singapore. And since Singapore is also an Asian city, that paper and the current study do have some overlapping research interests. On the other hand, there are important differences between the two papers. First, HL only studies HCCAPM while this paper studies several versions of consumption-based models (such as the habit formation model, recursive utility model, collateral constraint model, etc.). Second, the major objective of HL is to examine the asset market implications of the discretionary land supply policy of the Singapore government, while this paper is more concerned on the overall ability for consumption-based models to explain the asset prices. Notice that more than 80% of the Singapore population live in the subsidized-ownership housing units provided by the government and hence it is very sensible to study the government policy in the context of Singapore. On the other hand, subsidized-ownership housing units account for roughly 15% of the population of Hong Kong.[8] The housing markets of the two cities are indeed very

[8] Among others, see Leung and Tang (2012, 2014) for more discussion.

different. Third, HL is basically a calibration exercise. They use both VAR and OLS to estimate certain parameter values, and then simulate their models with those values in their models. On the other hand, this paper applies the same GMM estimation approach on a collection of consumption-based models and compares the model performance. In fact, to facilitate the comparison of model performance, this paper employs two different types of model comparison method, which is by nature very different from the model assessment scheme used in HL. Thus, the two papers indeed take very different approaches and could be interpreted as complementary.[9]

The structure of the paper is as follows: Section 2 will briefly provide the details of each model to be compared; Section 3 will display the GMM estimation results; Section 4 will explain the two criteria of model comparison and the corresponding results. Section 5 concludes. And the derivation or mathematics details are provided in the appendix.

2. MODELS

The several variants of consumption-based models of asset prices that will be considered in this paper share a few common features. Most of them are representative agent, frictionless models in which forward-looking agents make optimal consumption allocation by trading a full set of contingent consumption claims. These models imply that, although returns can vary across assets, expected discounted returns should always be the same for every traded asset:

$$1 = E_t(M_{t+1}R_{t+1}^i) \quad i = 1, 2, ..., N. \tag{1}$$

where R_{t+1}^i is the one-period (gross) rate of return of asset i and M_{t+1} is a stochastic discount factor (SDF) that can be identified with the representative agent's intertemporal marginal rate of substitution between consumptions at date t and t+1.[10] In our empirical analysis we focus on two asset returns, namely, stock return R_{t+1}^s and housing return R_{t+1}^h, and the associated Euler equations $1 = E_t(M_{t+1}R_{t+1}^s)$ and $1 = E_t(M_{t+1}R_{t+1}^h)$. As each model implies a different SDF, we can then compare the performance of various asset pricing models

[9] Clearly, we are not the first paper to study the asset markets of Hong Kong neither. Previous Asian studies, on the other hand, tend to use a reduced form approach and hence this study can be complementary to that literature. Among others, see Chang et al (2012, 2013).

[10] See Hansen et al. (2007) and Ludvigson (2012) for surveys of the consumption-based asset pricing literature.

based on evaluation criteria derived from the two Euler equations.

Notice that in (1) the SDF is common to *all* assets.[11] This suggests an analytical shortcut for the purpose of deriving the SDF. Rather than writing down a general model with many assets, it is sufficient to solve the representative agent's utility maximization problem with only one asset, in particular, the theoretical construct of the wealth portfolio which implies a very simple budget constraint.[12] This is the approach we are going to take in deriving the SDF anew for various consumption-based asset pricing models considered in this paper, some of which are generalization of existing models and have not appeared in the literature before. In addition to analytical tractability, this approach provides a common platform on which many diverse models from the literature can be naturally compared and understood, thereby significantly facilitates the identification of key features and insights most relevant for the present investigation. In what follows we will only outline the model setup, leaving the algebraic details to the appendix. Table 1 provides a one-line summary for each of the 8 consumption-based asset pricing models considered in this paper.

(Insert Table 1 here)

Notice that (1) is robust in the sense that it holds regardless the housing supply is endogenous or not. In the case of exogenous housing supply (e.g. the case of Piazzesi et al., 2007) (1) can be estimated directly with GMM. If housing supply is endogenous, then we should in principle estimate (1) jointly with the first order condition pertaining to the real estate developers. In the current context, the amount of new housing supply is very small relative to the stock during our sampling period.[13] Figure 1 shows that in HK, quarterly changes in housing price are many times more volatile than housing supply, suggesting that housing returns are mainly demand determined. Moreover, the Hong Kong government only provides data of the amount of new housing supply in annual frequency, which does not match the quarterly frequency of other data series in this paper. Casual observations also suggest that new housing supply is not evenly distributed over time, due to seasonal (such as

[11] The existence and uniqueness of SDF follows from the absence of arbitrage opportunities in frictionless markets (Hansen and Richard, 1987). In particular, the complete market assumption is necessary for the uniqueness of SDF.

[12] Among others, see Singleton (2006) for a discussion of alternative empirical practices in the literature.

[13] Among others, see Leung and Tang (2012, 2014) for an updated analysis of the housing supply in Hong Kong.

Christmas and Chinese New Year) or institutional reasons (for instance, students do not go to school in the summer and hence some households are more willing to move during summer).[14] It means that if we use interpolation on the annual housing supply series, we might introduce measurement errors into the model. In light of these constraints, it seems reasonable to treat housing supply as exogenous, at least for our purpose of explaining quarterly returns.

(Insert Figure 1 here)

We now outline the consumption-based models that will be compared among themselves.

Model 1: CCAPM

This is a one-good model in which the representative agent maximizes lifetime utility that is separable over time and across states of nature:

$$E_t \sum_{j=0}^{\infty} \beta^j u(C_{t+j}) \equiv V_t = u(C_t) + \beta E_t V_{t+1}, \quad \text{where } u(c) = \frac{c^{1-\rho} - 1}{1-\rho} \tag{2}$$

where $0 < \beta < 1$ is the discount factor; $\rho \geq 0$ doubles as the coefficient of relative risk aversion and the inverse elasticity of intertemporal substitution; and C_t is real consumption in nondurables and services. The representative agent's utility maximization problem with the wealth portfolio being the only asset is characterized by the Bellman equation

$$V(x_t, z_t) = \max_{C_t} \{u(C_t) + \beta E_t V(x_{t+1}, z_{t+1})\} \quad \text{subject to } x_{t+1} = R_{t+1}(x_t - C_t) \tag{3}$$

where x_t is the wealth portfolio that delivers the entire consumption stream C_t as the dividend; R_{t+1} is the gross rate of return of the wealth portfolio; and z_t is an exogenous Markovian random shock driving the wealth return. Solving the Bellman equation results in an Euler equation for asset return that looks like (1) with the SDF being

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\rho} . \tag{4}$$

Model 2: HCCAPM

[14] Among others, see Harding et al. (2003).

This is a two-good generalization of CCAPM by Piazessi et al. (2007). The representative agent's lifetime utility is the same as in (2) but C_t is now an aggregate of non-housing consumption c_t and housing service consumption s_t:

$$C_t = g(c_t, s_t) = \left(c_t^{1-\phi} + \omega s_t^{1-\phi}\right)^{1/(1-\phi)} \qquad \omega > 0, \quad \phi \geq 0 \tag{5}$$

Piazessi et al. (2007) derives the asset pricing equations for stock and housing explicitly by writing down a two-good Lucas tree model. We instead take the shortcut of the wealth portfolio approach to find out the appropriate SDF and then simply apply (1) to stock and housing returns. The representative agent's utility maximization problem is characterized by the Bellman equation

$$\begin{aligned} &V(x_t, z_t) = \max_{c_t, s_t} u(C_t) + \beta E_t V(x_{t+1}, z_{t+1}) \text{ subject to} \\ &\qquad x_{t+1} = R_{t+1}(x_t - c_t - q_t s_t) \text{ and } C_t = g(c_t, s_t) \end{aligned} \tag{6}$$

where non-housing consumption is designated to be the numeraire, and q_t is the relative price of housing service or the rental rate. We show in the appendix that the SDF for the HCCAPM model is

$$M_{t+1} = \beta \left(\frac{c_{t+1}}{c_t}\right)^{-\rho} \left(\frac{\alpha_{t+1}}{\alpha_t}\right)^{\frac{\rho-\phi}{1-\phi}} \tag{7}$$

where $\alpha_t = c_t / (c_t + q_t s_t)$ is the ratio of non-housing consumption to total consumption. Compared with the canonical CCAPM case in (4) where consumption growth is the only risk factor, agents in this case also care about composition risk – the variability of the relative weight between housing and non-housing consumption.

Model 3: Habit Formation

We consider a simple version of the habit formation model *a la* Abel (1990), Constantinides (1990), Campbell and Cochrane (1999), among many others. The representative agent's expected lifetime utility is the same as in (2) but $C_t = c_t / X_t$, a ratio of current consumption c_t to a benchmark or habit consumption level $X_t = (\bar{c}_{t-1})^{\kappa}$ taken to be exogenous by the representative agent, where $\bar{c}_{t-1}$ is economy-wide past consumption. The representative agent's problem is characterized by the Bellman equation

$$V(x_t, z_t) = \max_{c_t} \{ u(c_t / X_t) + \beta E_t V(x_{t+1}, z_{t+1}) \} \text{ subject to } x_{t+1} = R_{t+1}(x_t - c_t) \tag{8}$$

Solving the Bellman equation and imposing the equilibrium condition $\overline{c}_t = c_t$ result in an Euler equation for asset return with the SDF being

$$M_{t+1} = \beta \left(\frac{c_{t+1}}{c_t} \right)^{-\rho} \left(\frac{c_t}{c_{t-1}} \right)^{\kappa(\rho-1)} \tag{9}$$

Compared with CCAPM, the habit formation mechanism in this model introduces time-non-separability into preferences and the SDF ends up with having lagged consumption growth as an additional risk factor.

Model 4: H-habit Formation

This is a hybrid of HCCAPM and habit formation which has not appeared in the literature before, to the best of our knowledge. The representative agent's expected lifetime utility is the same as in (2) but

$$C_t = g(c_t, s_t) / X_t, \quad g(c_t, s_t) = \left(c_t^{1-\phi} + \omega s_t^{1-\phi} \right)^{1/(1-\phi)}, \text{ and } X_t = g(\overline{c}_{t-1}, \overline{s}_{t-1})^{\kappa} \tag{10}$$

where $\overline{c}_{t-1}$ and $\overline{s}_{t-1}$ are lagged economy-wide non-housing and housing consumption treated as exogenous by the representative agent. The representative agent's problem is characterized by the Bellman equation

$$\begin{gathered} V(x_t, z_t) = \max_{c_t, s_t} u(C_t) + \beta E_t V(x_{t+1}, z_{t+1}) \text{ subject to} \\ x_{t+1} = R_{t+1}(x_t - c_t - q_t s_t) \text{ and } C_t = g(c_t, s_t) / X_t \end{gathered} \tag{11}$$

which implies an Euler equation for asset return with the SDF being

$$M_{t+1} = \beta \left(\frac{c_{t+1}}{c_t} \right)^{-\rho} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{\rho-\phi}{1-\phi}} \left(\frac{c_t}{c_{t-1}} \right)^{\kappa(\rho-1)} \left(\frac{\alpha_t}{\alpha_{t-1}} \right)^{\frac{\kappa(1-\rho)}{1-\phi}} \tag{12}$$

Clearly this SDF is a mixture of the corresponding expressions in (7) for HCCAPM and in (9) for the habit formation model. As expected, the habit formation mechanism introduces time-non-separability into the HCCAPM model, thereby making lagged consumption growth and lagged expenditure share growth as additional risk factors in the SDF.

Model 5: Recursive Utility

Let V_t be the lifetime utility as of date *t* of the representative agent. The recursive utility model of Epstein and Zin (1989, 1991) and Weil (1989) defines V_t by the recursion

$$V_t = \left[(1-\beta)C_t^{1-\rho} + \beta\left(E_t V_{t+1}^{1-\sigma}\right)^{(1-\rho)/(1-\sigma)}\right]^{1/(1-\rho)} \equiv F(C_t, \mu_t(V_{t+1})) \qquad (13)$$

where $\mu_t(V_{t+1}) = (E_t V_{t+1}^{1-\sigma})^{1/(1-\sigma)}$ is the certainty equivalent of future utility or continuation value; $0 < \beta < 1$ is the discount factor; $\sigma \geq 0$ is the coefficient of relative risk aversion; and $\rho \geq 0$ is the inverse elasticity of intertemporal substitution. With recursive preferences the representative agent is no longer indifferent between the timing of resolution of uncertainty; in particular, when $\sigma > \rho$ the agent prefers early resolution. When $\sigma = \rho$ the CCAPM model emerges as a special case because (13) reduces to

$$J_t = (1-\beta)C_t^{1-\rho} + \beta E_t J_{t+1} = (1-\beta)\sum_{j=0}^{\infty}\beta^j C_{t+j}^{1-\rho}, \text{ where } J_t = V_t^{1-\rho} \qquad (14)$$

which is nothing but a scaled version of (2). The representative agent's utility maximization problem can be characterized by the Bellman equation

$$V(x_t, z_t) = \max_{C_t} F(C_t, \mu_t[V(x_{t+1}, z_{t+1})]) \text{ subject to } x_{t+1} = R_{t+1}(x_t - C_t) \qquad (15)$$

which implies an Euler equation for asset return with the SDF being

$$M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\rho}\left(\frac{V_{t+1}}{\mu_t(V_{t+1})}\right)^{\rho-\sigma} = \left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\rho} R_{t+1}\right]^{\frac{1-\sigma}{1-\rho}} R_{t+1}^{\;-1} \qquad (16)$$

To empirically implement (16) one will have to construct the aggregate wealth return. Epstein and Zin (1991) use the value-weighted NYSE stock market return as a proxy. This approach can be criticized by noting that other important assets such as human capital and housing are not included in the stock index return, although they may be correlated with stock index return to some degree. In our empirical work, we follow Campbell (1996) to measure the aggregate wealth return by a weighted average of stock index return, labor income growth (as a proxy for human capital return), and housing return.

Model 6: H-Recursive Utility

This is the recursive utility analogue of the HCCAPM model in Fillat (2007) and Zhang

(2009). The representative agent's lifetime utility is the same as in (13) with C_t being an aggregate of non-housing consumption and housing service consumption as stated in (5). With non-housing consumption designated to be the numeraire, the representative agent's utility maximization problem is characterized by the Bellman equation

$$\begin{aligned} &V(x_t, z_t) = \max_{c_t, s_t} F(C_t, \mu_t[V(x_{t+1}, z_{t+1})]) \text{ subject to} \\ &\qquad x_{t+1} = R_{t+1}(x_t - c_t - q_t s_t) \text{ and } C_t = g(c_t, s_t) \end{aligned} \tag{17}$$

where q_t is the relative price of housing service or the rental rate. We show in the appendix that the SDF for the H-recursive utility model is

$$M_{t+1} = \left[\beta\left(\frac{c_{t+1}}{c_t}\right)^{-\rho} R_{t+1}\right]^{\frac{1-\sigma}{1-\rho}} R_{t+1}^{-1}\left(\frac{\alpha_{t+1}}{\alpha_t}\right)^{\frac{\rho(1-\sigma)-\phi(1-\rho)}{(1-\phi)(1-\rho)}} \tag{18}$$

Model 7: Labor Income

Davis and Martin (2009) introduce leisure into the Piazzesi et al. (2007) HCCAPM setup, expanding it to a three-good model. The representative agent's lifetime utility is the same as (2) with the consumption index C_t being an aggregate of leisure n_t, non-housing consumption c_t, and housing service consumption s_t:

$$C_t = g_t n_t^{\nu}, \text{ where } g_t \equiv g(c_t, s_t) = \left(c_t^{1-\phi} + \omega s_t^{1-\phi}\right)^{1/(1-\phi)} \tag{19}$$

There are two layers of aggregation in (19). The first layer aggregates non-housing and housing consumption by the CES function $g_t \equiv g(c_t, s_t)$ as in Piazzesi et al. (2007). In the second layer g_t and leisure are aggregated into C_t by a Cobb-Douglas function with relative weight *v*. Davis and Martin (2009) derive explicitly the asset pricing equations for stock portfolios, housing, and other assets by writing down a Lucas-tree typed model with many assets. We instead take the shortcut of the wealth portfolio approach with only one asset and hence derive the corresponding SDF comparable to the other models. The representative agent's utility maximization problem is characterized by the Bellman equation

$$V(x_t, z_t) = \max_{c_t, s_t, n_t} u(C_t) + \beta E_t V(x_{t+1}, z_{t+1}) \text{ subject to}$$
$$x_{t+1} = R_{t+1}(x_t - c_t - q_t s_t + w_t(1 - n_t)) \text{ and } C_t = g(c_t, s_t) n_t^{\nu} \tag{20}$$

where q_t is the relative price or rental rate of housing service, w_t is the real wage, and the agent's time endowment has been normalized to 1. In the appendix we show that the SDF in this case extends the corresponding HCCAPM expression in (7) by adding labor income growth as an additional risk factor:

$$M_{t+1} = \beta \left(\frac{c_{t+1}}{c_t} \right)^{-\rho - \nu(1-\rho)} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{\rho-\phi}{1-\phi} + \nu(1-\rho)} \left(\frac{w_{t+1}}{w_t} \right)^{-\nu(1-\rho)} \tag{21}$$

Model 8: Collateral Constraint

We extend the housing-collateral constraint model of Iacoviello (2004) to three assets (real estate, risk-free bond, and stock) with heterogeneous agents and limited asset market participation. The pure endowment, Lucas-tree economy is populated by two types of agents. The first type is forward-looking, unconstrained agents who participate actively in all three asset markets and the rental market to optimally allocate housing and non-housing consumption over time. The second type is myopic, constrained agents who can only borrow with collateral constraints tied to their home values and do not participate in the stock market and the rental market. With non-housing consumption designated to be the numeraire, the utility maximization problems of the two types of agents are as follows:

Unconstrained agents: Choose non-housing consumption C_t^u, housing service consumption S_t^u, borrowing B_t^u, real estate holdings H_t^u and stock holdings F_t^u, for all t ≥ 0, to maximize discounted lifetime utility

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{(C_t^u)^{1-\rho} - 1}{1-\rho} + \chi \frac{(S_t^u)^{1-\theta} - 1}{1-\theta} \right] \tag{22}$$

subject to

$$C_t^u + q_t S_t^u + P_t^h H_t^u + P_t^s F_t^u + R_{t-1} B_{t-1}^u = B_t^u + Y_t^u + (P_t^h + q_t) H_{t-1}^u + (P_t^s + d_t) F_{t-1}^u,$$
$$H_{-1}^u, B_{-1}^u, F_{-1}^u \text{ given; } t = 0,1,2,... \tag{23}$$

where Y_t^u is exogenous endowment; R_{t-1} is the risk-free interest rate paid on loans made between t-1 and t; P_t^s is the share price of a stock (Lucas tree) that pays dividend d_t per share; P_t^h is the unit price of a house (effectively a second Lucas tree) which bears 1 unit of housing service that sells for q_t in the rental market.

Constrained agents: For each period $t \geq 0$, choose non-housing consumption C_t^c, borrowing B_t^c, and real estate holdings H_t^c to maximize

$$\frac{(C_t^c)^{1-\rho}-1}{1-\rho}+\chi\frac{(H_t^c)^{1-\theta}-1}{1-\theta} \tag{24}$$

subject to

$$C_t^c + P_t^h(H_t^c - H_{t-1}^c) + R_{t-1}B_{t-1}^c = B_t^c + Y_t^c, \quad H_{t-1}^c, B_{t-1}^c \text{ given.} \tag{25}$$

$$B_t^c \leq mE_t(P_{t+1}^h)H_t^c / R_t \tag{26}$$

where we have assumed constrained agents are all owner-occupiers. (24) says that constrained agents are myopic and they only care about today's utility. (26) is a borrowing constraint that limits the amount of loans to a fraction m ≤ 1 of the next period's expected value of real estate holdings discounted by the rate of interest. In other words, constrained agents can only borrow with their houses posted as collateral. The model is closed by assuming the observed aggregate consumption to be a geometric average of the consumption of the two types of agents:

$$C_t = (C_t^c)^{\lambda}(C_t^u)^{1-\lambda}, \quad 0<\lambda<1. \tag{27}$$

Following Iacoviello's (2004) procedure of loglinearizing first-order conditions and approximating expected log consumption growth by long-term interest rate, we show in the appendix that the returns of the three assets can be characterized by the following loglinear asset pricing equations:

$$\rho c_t = -(1-\lambda)(l_t + E_t r_{t+1}^i) + \lambda\omega(p_t + r_t - E_t p_{t+1}) + \lambda p_t + \lambda\theta h_t, \quad i=f,s,h \tag{28}$$

where all variables are measured in log deviation from steady state with r_{t+1}^i being the log return of asset i, c_t aggregate consumption, l_t long-term interest rate, p_t house price, and h_t the housing demand of constrained agents. The parameter $1+\omega \equiv (1-m\beta)^{-1}$ can be interpreted as the inverse of the down-payment needed to purchase one unit of housing. For the risk-free rate, $E_t r_{t+1}^f = r_t^f$, and eq. (28) reduces to Iacoviello's (2004) Euler equation.

3. DATA AND STRUCTURAL ESTIMATION

3.1 The data

We use Hong Kong quarterly data from 1983 to 2013 in this study. Details about data source and variable definition can be found in appendix B. The main variables that are used in our model comparison exercise include: (1) Stock return constructed from the Hang Seng stock market index and its dividend yield series; (2) Housing return for private domestic units constructed from disaggregated price and rent information for properties classified into 5 size-classes in 3 locations; (3) Growth rate of per capita consumption on food, non-durables and services; (4) The share of non-housing consumption expenditure in total consumption expenditure that includes an imputed housing component for owner-occupiers; (5) Wage growth; (6) Short (3-month) and long (10-year) risk-free rates. All variables are measured in real terms (2010 constant price) after inflation adjustment. Summary statistics of these variables can be found in Table 2.

(Insert Table 2 here)

A few observations are immediate and we begin our discussion with (3). According to Table 2, the non-housing consumption share of Hong Kong people is roughly 77%, which is 5% lower than the corresponding figure of the US (82%, reported in Piazessi et al., 2007, p.541), whereas the standard deviation is almost the same (about 0.03 for both countries). In other words, Hong Kong people allocate 5% more of their total consumption on housing than their US counterpart. It is consistent with the casual observation that, relative to the salary, the house price and rent are higher in Hong Kong.

The persistence among variables varies significantly. For instance, notice also that the first order autocorrelation of the non-housing consumption share is almost 0.98, suggesting that the division between housing versus non-housing in consumption is very stable over time.

On the other hand, the consumption growth, which is item (4), has a very low value in the first order autocorrelation. As a first order approximation, the aggregate consumption can therefore be treated as a random walk process.[15] The first order autocorrelation of the wage growth, which is item (5) is indeed negative. According to some previous studies such as Allen (1995), the wage growth tends to be correlated to the productivity growth. It would suggest that the productivity growth in Hong Kong is not persistent. On the other hand, the first order autocorrelation of the inflation rate, which is item (6), is about 0.36. The persistence of inflation rate seems to be consistent with other countries experience.[16]

We now turn to the asset returns, which are (1) and (2). Table 2 shows that the first order autocorrelation of the housing return is significant while the counterpart of the stock return is close to zero. It is similar to the consumption growth process, suggesting that it is indeed reasonable to conjecture that one can account for the stock return with consumption growth. Figure 2 depicts the return series. Consistent with the standard deviation and first-order autocorrelation statistics reported in Table 2, stock returns appear to be highly volatile and random-looking, whereas housing returns appear to be smoother and more persistent. To further our understanding of the two return series, we conduct some benchmark regressions and report the results in Table 3. Our choice of explanatory variables consists of those that typically mentioned in applied works and the press, including income growth, short and long interest rate, yield curve slope, and dummy variables meant to capture unexpected events such as natural disasters and other crises. Notice that the intercept terms in all 4 regressions are not statistically different from one, reflecting our usage of gross rather than net return data. For the two stock return regressions, although the estimated coefficients of GDP growth and the interest rate variables are of the expected sign, none of them are statistically significant. The Durbin-Watson (DW) statistic indicates there is no strong evidence of serial correlation in the residuals, implying that stock returns are essentially

[15] Notice that if a variable (in log form) is approximated by the random walk process, $X_t = X_{t-1} + U_t$ where U_t is a white noise, then as we regress $\Delta X_t = \rho \Delta X_{t-1} + (residual)$, where $\Delta X_t \equiv X_t - X_{t-1}$, it is effectively regressing $U_t = \rho U_{t-1} + (residual)$, and the estimated ρ will be very small. This observation has been explored by many authors, starting with Hall (1978). Among others, see Campbell and Mankiw (1989) for more discussion on this point.

[16] Among others, see Krause et al. (2008) on the inflation dynamics of the U.S. For a discussion of some recent development in inflation dynamics, see Oinonen et al. (2013), among others.

unpredictable by its own past, or equivalently, the stock market index behaves like random walk. It is consistent with the notion that the Hong Kong's stock market is rather efficient and arbitrage opportunities are quickly exploited, an expected result in view of Hong Kong being an international financial center with a well-developed stock market.[17] In contrast, the two housing return regressions exhibit exactly the opposite pattern--statistically significant GDP growth and interest rate variables, plus DW way below 2—which implies strong serial correlation in the housing return series, suggesting market imperfections or other inefficiencies (such as high transaction cost and government interference) in Hong Kong's property market.[18] Finally, it is interesting to see that the likelihood ratio test strongly supports using the yield curve slope, rather than interest rates of different maturities, as the relevant interest rate variable to explain asset returns.

(Insert Figure 2 here)

(Insert Table 3 here)

3.2 Structural estimation results

We apply GMM to estimate the 8 consumption-based models of asset prices. The conditional moment conditions that we use in the GMM estimation are two Euler equations—one for stock return and the other for housing return—derived from each model as shown in section 2. That is, for each model, the GMM procedure will look for one set of best-fitting structural parameter estimates that can explain *both* stock and housing returns. This is more demanding, but more reasonable, than estimating the two Euler equations separately which will give two different sets of structural parameter estimates for the same model. In order to facilitate comparison across models, we summarize in Table 3 the economic interpretation of the structural parameters in different models. The GMM estimation results are reported in Table 5.

(Insert Table 4 here)

(Insert Table 5 here)

We can see from the estimation results that, in general, the models are internally consistent—the Hansen over-identification J-statistics are all insignificant at conventional

[17] For more discussion of the efficient market hypothesis, see Fama (1970), Malkiel (2003), among others.

[18] Among others, see Case and Shiller (1989), Chang et al. (2012, 2013) for related discussion.

level, suggesting valid moment conditions. The models also produce economically reasonable parameter estimates: the estimated parameters actually belong to the intervals of parameter values suggested by the macro literature. For instance, after taking into account standard errors, the estimated discount factors are all around (0.95,1), which is consistent with the macro literature theoretical discount factor. The relative risk aversion values generally belong to (0,10), which also matches the consumption-based asset pricing literature. For the two recursive utility models, which disentangle relative risk aversion and elasticity of intertemporal substitution, the result $\hat{\sigma} > \hat{\rho}$ implies that Hong Kong people prefer early resolution of uncertainty, a crucial condition underlying the long run risks model of Bansal and Yaron (2004) which has been found successful in resolving the equity premium puzzle and other anomalies in asset prices.[19] Finally, from the estimation results of the collateral constraint model, it is interesting to see that the fraction of liquidity constrained households λ is estimated to be 0.4784 (with standard error 0.13), which is higher than Iacoviello's (2004) estimate of 0.26 (with standard error 0.08), but closer to the range of Campbell and Mankiw's (1989) estimates in the neighborhood of 0.4.

4. MODEL COMPARISON

The previous section has shown that the 8 asset pricing models in general are not rejected by the data according to the GMM estimation results. Yet the models are indeed different. Thus, it is natural to ask which model provides a better description of the data. And since GMM cannot distinguish which model performs better, we need to adopt other criteria for model comparison.

We employ two model comparison criteria in this section: the comparison of "prediction errors" based on theory-motivated loglinear reduced form equation and the Hansen-Jagannathan (1997) HJ-distance.[20] The two criteria focus on different characteristics

[19] As we will explain in a later section, this finding is important for understanding why the two recursive utility models do so well in the model comparison exercise.

[20] We should qualify that the "prediction" throughout this paper means prediction of the next period asset price based on the current and previous period asset prices, and the model and parameter values estimated using the

of a theoretical model, and we can view them as complementary to each other. For example, comparing reduced form equations is more robust to specification errors and restrictive functional form in the theoretical models, but it is essentially a model comparison method for linear models, and hence may not capture the structural characteristics of the nonlinear Euler equations. Thus, we also apply the HJ-distance method as well which is specifically designed for measuring Euler equation errors with all structural characteristics preserved.

4.1 Theory-motivated loglinear reduced form equation

Under the assumptions of lognormality and conditional homoscedasticity,[21] the Euler equation $1 = E_t(M_{t+1}R_{t+1}^i)$ can be rewritten as

$$E_t m_{t+1} + E_t r_{t+1}^i + \tfrac{1}{2}(\sigma_m^2 + \sigma_i^2 + 2\sigma_{im}) = 0 \qquad (29)$$

where m_{t+1} and r_{t+1}^i are the logarithm of M_{t+1} and R_{t+1}^i respectively; σ_m^2 and σ_i^2 are the unconditional variance of m_{t+1} and r_{t+1}^i, and σ_{im} is their unconditional covariance. Observe that $E_t r_{t+1}^i$ is the one-step ahead forecast of the log-return of asset i. Thus, the loglinear Euler equation (29) can in principle generate forecasts for log-return, provided that a forecast of the log SDF m_{t+1} is available. In section 2 we have derived analytical expressions for the SDF of the 8 models and they are all loglinear in observables. For example, we show in (7) the SDF of the HCCAPM model is loglinear in consumption growth c_{t+1}/c_t and non-housing consumption share growth α_{t+1}/α_t, and the model's loglinear Euler equation is

$$E_t r_{t+1}^i = \phi_0 + \phi_1 E_t \ln(c_{t+1}/c_t) + \phi_2 E_t \ln(\alpha_{t+1}/\alpha_t) \qquad (30)$$

where (ϕ_0, ϕ_1, ϕ_2) are complicated functions of the structural parameters. If we insert forecasts for log consumption growth and share growth on the right hand side, (30) will imply a reduced form forecasting equation for log-return. The least square residuals from such a forecasting equation will give log-return prediction errors. However, this is not a good

whole sampling period, and is therefore of the in-sample goodness-of-fit type, rather than the out-of-sample type forecasting.

[21] On top of its popularity in applied studies, lognormal AR assumption has some nice properties in terms of temporal aggregation. Among others, see Salazar and Ferreira (2011) for more details.

approach for the purpose of model comparison, because it is not clear whether the prediction errors are due to deficiency in the HCCAPM model per se or due to the poor forecasts of log consumption growth and share growth that we superimpose on the forecasting equation. A better approach, at least for model comparison purpose, is to "give the model the best chance" by using the observed consumption growth and share growth in place of their forecasts on the right-hand-side of (30). By doing so we can then attribute the log-return prediction errors to the HCCAPM model alone.

We apply the methodology described in the last paragraph to each of the 8 asset pricing models and generate their log-return prediction errors. For benchmarking we also include a pure statistical AR(1) model that is not motivated by any theory. Tables 6 and 7 report the estimated loglinear reduced form equations of the 8 asset pricing models. The prediction performance of the models is compared in terms of 4 measures: mean squared errors (MSE), mean absolute errors (MAE), Akaike information criterion (AIC), and (Schwarz) Bayesian information criterion (BIC). MSE and MAE correspond to alternative loss functions which penalize prediction errors in different ways. In particular, MSE penalizes more heavily large prediction errors than small ones, whereas MAE treats large and small prediction errors in a more symmetrical manner. AIC and BIC penalize large model size while rewarding small MSE. They are especially useful in comparing the original and the housing-augmented version of the same asset pricing model. Since the housing-augmented version always has more explanatory variables in the loglinear reduced form equation than the original model does, it will by construction attain a smaller MSE which may mislead us into believing that the housing-augmented version always beats the original version.

Table 8 reports the four prediction performance measures for the models, separately in two panels for stock return and housing return. A qualitative summary of the models' ranking can be found in Table 11. The following observations emerge from the prediction performance comparison:

(a) Considering the cases of HCCAPM vs. CCAPM, H-Habit vs. Habit, and H-Recursive vs. Recursive, AIC and BIC indicate that the inclusion of housing always improve the prediction of housing return but not necessarily so for predicting stock return. In fact, for

Habit and CCAPM, *the inclusion of housing worsens the prediction of stock return*.[22] This means that the Piazzesi et al. (2007) insight of composition risk (as captured by nonhousing consumption share growth) is an important source of risk in pricing housing return, but not necessarily so in pricing stock return. To put it in another way, there may be asset-specific factors in explaining different asset returns.[23]

(b) Among the 8 structural models considered, the two recursive utility models are the best in predicting stock return, irrespective of prediction performance criteria. This implies that breaking the tight link between risk aversion and the elasticity of intertemporal substitution (EIS) is important for structural modeling of stock return data.

(c) For both stock and housing returns, AIC and BIC indicate that the two recursive utility models always beat their non-recursive utility counterparts, given the same risk factors in the SDF, i.e. H-Recursive vs. HCCAPM, Recursive vs. CCAPM. This corroborates the GMM estimation results of the two recursive utility models in Table 5 that the risk aversion parameter σ and the reciprocal of EIS ρ are statistically different from each other.

(d) Adding labor income risk on top of consumption growth and composition risk *does not* improve prediction performance, for both stock and housing returns. We can see this clearly by comparing the AIC and BIC of the labor income model vs. HCCAPM, since the latter is a special case of the former.

(e) The collateral constraint model is the best in predicting housing return, irrespective of prediction performance criteria, but its ranking drops to the middle range in stock return prediction. This suggests that taking into account financial market imperfection should play an important role in structural modeling of housing return data. On the other hand, as far as modeling stock return is of concern, the role of market imperfection may be secondary to a more realistic specification of agents' attitude towards risk and uncertainty as in the recursive utility model.

[22] Recall that the share of housing vs non-housing consumption is very persistent in the Hong Kong data (Table 2). It is then not surprising that the composition risk is not that important, at least for the Hong Kong data.

[23] Consistent with this hypothesis, Chang et al. (2011) find that while innovations in term spread are important in explaining both REIT return and housing return in the U.S. in a VAR setting, they have virtually zero impact on the U.S. stock return. To the extent that there are asset-specific factors in explaining returns, it is conceivable that an asset pricing model which performs well in forecasting stock return may not do so for housing return. More discussion on this to be followed.

(Insert Tables 6 - 8 here)

We have shown that the 8 models are indeed different in terms of their ability in explaining the stock and housing returns. It is natural to ask whether such differences are statistically significant, after allowing for the randomness in the data. To address this issue, we apply the multiple forecast comparison procedure proposed by Mariano and Preve (2012) which is a special case of the more general *model confidence set* (MCS) procedure of Hansen, Lunde and Nason (2011). The Mariano-Preve procedure is based on (1) an *equal predictive ability* (EPA) chi-squared test which is a multivariate generalization of the Diebold-Mariano (1995) test for comparing two forecasting models, and (2) an *elimination rule* that removes the weakest model in the event that the null hypothesis of EPA is rejected. Let M_0 be a collection of N models under comparison. The goal is to select a subset M* of models that are statistically indistinguishable (i.e. they form an MCS). The Mariano-Preve procedure iterates around the following steps:

Step 0. Sort the N models by the (observed) performance criterion (MSE, for example) and label them from #1 to #N, with #1 being the best. Initially set $M = M_0$.

Step 1. Test the null hypothesis of EPA for the models in M.

Step 2. If the EPA hypothesis accepted, define M* = M; otherwise, eliminate the worst model from M and repeat the procedure from Step 1.

After M* has been found, one can apply the algorithm again to the complement $M_1 = M_0/ M^*$ to check if a second MCS can be found. By this algorithm the N models will be classified into J model confidence sets ordered from the best to the worst: $M_1^* \succ M_2^* \succ \cdots \succ M_J^*$.

Table 9 reports the results of the Mariano-Preve procedure based on the performance criteria of MSE and MAE, for stock and housing returns, respectively. A qualitative summary of the conclusion can be found in Table 11. In Table 9 panel A, the models are compared according to their stock return prediction performance under the MSE criterion. When all 9 models are under comparison, the null hypothesis of model equivalence is strongly rejected by the MP test whenever the two recursive utility models (i.e. model #1 and #2) are included together with other models, whereas the null hypothesis of models #1 and #2 being equivalent is marginally accepted (p-value = 0.0564). This suggests a two-set classification scheme: {#1 and #2} ≻ {#3 to #9}, that is, the two recursive utility models belong to one MCS and the remaining 7 models belong to another. The remaining two columns in Table 9 panel A show that no further sub-divisions can be found. In the middle column, when only model #1 is excluded from the comparison, the null hypothesis of model equivalence is always strongly rejected, confirming that model #2 is indeed different from models #3 - #9. In the last column, when both models #1 and #2 are excluded from the comparison, the null hypothesis of model equivalence can no longer be rejected, confirming that models #3 - #7 indeed belong to one MCS. Exactly the same two-set classification scheme emerges from Table 9 panel B in which the models are compared according to their stock return prediction performance under the MAE criterion. In summary, we can conclude that, the two recursively utility models are significantly better than the remaining 7 models in stock return prediction after taking random errors into consideration.

Table 9 panel C compares the housing return prediction performance of the models under the MSE criterion. When all 9 models are under comparison, the null hypothesis of model equivalence is always strongly rejected, suggesting that model #1 (collateral constraint model) stands out from the crowd, i.e. {#1} ≻ {#2 to #9}. When model #1 is excluded from the comparison, the null hypothesis of model equivalence is rejected at more or less 5% significance level sequentially until only models #2 and #3 remain, suggesting that the set {#2 to #9} can be subdivided into two: {#2 and #3} ≻ {#4 to #9}. The last column in panel C confirms that the set {#4 to #9} cannot be subdivided anymore, as none of the model equivalence tests is statistically significant. A slightly different classification emerges from Table 9 Panel D in which the models are compared according to their housing return prediction performance under the MAE criterion. The results indicate unambiguously a two-set classification scheme: {#1} ≻ {#2 to #9}. In summary, we can conclude that the collateral constraint model is significantly better than the remaining 8 models in housing return prediction under both MSE and MAE criteria, even after allowing for random errors. Under the criterion of MSE, the H-habit and H-Recursive model form another MCS whose housing return prediction performance is second to that the collateral constraint model.

(Insert Table 9 here)

Finally, in order to better understand the nature of the prediction errors, in Figures 3 and 4 we plot the time series of the absolute prediction errors for each model. Notice that we intentionally use the same scale across models to facilitate a "visual comparison". It is clear from Figure 3 that the Recursive Utility model and its housing-augmented counterpart produce much smaller prediction errors, which confirms the previous tables that they indeed outperform other models in stock return prediction. In Figure 4 it can be seen that the collateral constraint model produce smaller absolute prediction errors, again confirming the findings reported in previous tables.

(Insert Figure 3 and 4 here)

Now, based on these graphs and drawing on our knowledge about the history of Hong Kong's economy during the sample period, we provide the following remarks for the stock return prediction:

(1) Except for the Recursive utility model, all other models have relatively bigger absolute prediction errors in the four time periods: the years of 1987, 1993, 1998, 2008. These four time periods were all related to some large economic or political issues in Hong Kong. For instance, on the "Black Monday," i.e. 19th October, 1987, stock markets around the world, including the Hong Kong one, crashed and shed a huge value in a very short time.[24] In 1993, there was what investment world called the "Morgan shock", which refers to the famous investment bank Morgan Stanley as the leading investment bank landed in Hong Kong and created huge volatility to Hong Kong's stock market. In 1998, after the political handover of Hong Kong to mainland China, the Asia Financial Crisis occurred. A "Storm of Hedge Fund" created by George Solos made Hong Kong's stock market very volatile.[25] In 2008, the global financial crisis again shocked Hong Kong's stock market. The appearance of larger absolute prediction errors during these four time periods means that these consumption-based asset pricing models, except for the recursive utility model, are unable to capture stock price volatility due to "rare disasters".

(2) Notice that among all the models we consider, only the recursive utility model and its housing-augmented counterpart would separate the elasticity of intertemporal substitution and

[24] See Carlson (2006) for a detailed review of the event.

[25] Among others, see Sheng (2009) for a detailed discussion.

the degree of risk aversion. For a small open economy like Hong Kong, “large external shocks” or “rare disasters” would have significant impact to the asset markets. In this case, the timing of uncertainty resolution matters, and only recursive utility models can possibly capture that and this could be the reason why they outperform other models.[26]

(3) Figure 4 shows that the collateral constraint model outperforms other models in predicting housing return. It means that collateral constraint is important (Kiyotaki and Moore, 1997). It is also consistent with the general modelling results of Chen and Leung (2008), Funke and Paetz (2013). In Hong Kong, the Hong Kong Monetary Authority (HKMA) enforces all banks to issue mortgages with at least 30% downpayment, which is significantly higher than many advanced economies. “Subprime loans” do not exist in Hong Kong. And given that the income-to-house price ratio is relatively low in Hong Kong (Leung and Tang, 2014), it is not surprising that many households are not able to participate in the housing market, except with strong family support or extraordinary investment return. In reviewing the Hong Kong experience in combating financial crises, a former official in the HKMA, Dr. Dong He, admits that maintaining a high down-payment ratio is an intended policy measure. He (2013) writes that “…The financial policy framework in Hong Kong emphasizes the importance of limiting the degree of leverage on the balance sheets of both the private and public sectors so that households, firms, and the government can weather financial cycles… the external shock of the Asian financial crisis prompted a collapse of the property market: housing prices dropped by 66 percent, output contracted by 9 percent in total over five quarters and remained more or less flat for seven years… What is more interesting was the very low mortgage delinquency ratio that peaked at 1.4 percent despite the 66 percent correction in property prices. There was no banking crisis and there was no need to bail out banks. This is in sharp contrast to the banking and financial crisis in the United States and Europe after Lehman’s collapse, where housing prices dropped less significantly but the delinquency ratios increased more sharply… A range of factors had contributed to the relatively low mortgage delinquency ratio in Hong Kong after the bubble burst,… But an important factor was the macroprudential measure that capped the loan-to-value (LTV) ratio of mortgages at 70 percent. This provided banks with a

[26] See Epstein and Zin (1989, 1991) for the proof and more discussion on how the formulation of recursive utility function is related to the timing of uncertainty resolution.

significant cushion to absorb property-price correction, and a substantial equity stake that maintained incentives for borrowers to service loans as long as they were able to do so."[27]

4.2 Hansen-Jagannathan distance

The Hansen and Jagannathan (1997) (HJ) distance provides a measure of the misspecification errors of a SDF model.[28] It is defined as the minimized value δ of the following constrained least squares problem:

$$\text{Choose } m \text{ to minimize } \delta^2 = E(y-m)^2 \text{ subject to } E(mx) = q \tag{31}$$

where y is the SDF of the candidate model, x is a vector of asset payoffs, and q is a vector of the corresponding asset prices. Hansen and Jagannathan (1997) show that (31) has a closed-form solution and there are two alternative expressions for the (squared) HJ-distance. The first expression is

$$\delta^2 = E[y^2 - (y - \lambda' x)^2 - 2\lambda' q] \quad \text{where} \quad \lambda = (Exx')^{-1} E(xy - q) \tag{32}$$

In practice, (32) is approximated by replacing the population moments by sample moments, given time series data $\{y_t, x_t, q_t, t = 1, 2, ..., T\}$. The second expression is

$$\delta^2 = (Exy - Eq)'(Exx')^{-1}(Exy - Eq) \tag{33}$$

which can be interpreted as a weighted average of the pricing errors $E(xy - q)$.

In our empirical work we use stock and housing return data so that both x and q are 2 x 1 vectors, with q being a vector of 1's. For each asset pricing model we calculate its SDF series with unknown structural parameters replaced by the GMM estimates reported in Table 5. To account for random errors coming from the GMM parameter estimates and the data, we apply the Hansen, Lunde and Nason (2011) MCS procedure with a model equivalence chi-squared test constructed from (32) (see Appendix C for details). The iterative process follows exactly the same steps as in the Mariano-Preve procedure that we described above, with the only difference being the use of our own HJ-distance model equivalence test in step 1. The results are reported in Table 10 and a qualitative summary can be found in Table 11. The following

[27] For an assessment of the real impact of LTV ratio on the Hong Kong housing price, see Wong et al. (2014), among others.

[28] The HJ distance method does not apply to the collateral constraint model because this model does not have the basic form of SDF pricing kernel in its Euler equation.

observations emerge from the HJ-distance comparison:

(a) From the HJ-distance ranking, we see that the two recursive utility models occupy the top two spots and the small values of their HJ-distance compared with the rest suggest that they belong to a class of their own. This is confirmed by the Hansen-Lunde-Nason MCS procedure reported in the last two columns in Table 10. The iterative process of sequential testing and elimination of weak models unambiguously establishes the following two-set classification scheme: {Recursive, H-Recursive} ≻ {CCAPM, Habit, H-Habit, Labor income, HCCAPM}.

(b) A pairwise comparison of Recursive vs. H-Recursive, CCAPM vs. HCCAPM, and Habit vs. H-Habit suggests that the inclusion of housing can generate more "pricing errors" which inflate the HJ-distance. This is an interesting phenomenon which may appear to be contradictory to the result of housing return prediction by reduced form equation reported in section 4.1. We provide a potential explanation in next section when we discuss the fundamental difference between the methodologies of the two model comparison approaches.

(Insert tables 10 and 11 here)

4.3 Discussion

(a) More about the two model comparison methods and their results

While it is natural to expect different model rankings when different approaches are employed, it is instructive to discuss the methodological differences of the two model comparison methods. First, since the loglinear reduced form equation method is only based on linearized Euler equations, inevitably some structural information of the underlying theoretical model will be lost. On the other hand, the reduced form equation can be interpreted as a loglinear *approximation of a large family of models*, and hence will be less susceptible to specification errors and potentially unrealistic restrictions implied by theoretical model.[29] In contrast, HJ-distance preserves all the structural characteristics of the Euler equation, including those that come from specification errors and over-simplified assumptions in the theoretical model. This means that if the theoretical models are considered

[29] For instance, if the income tax schedule is highly nonlinear, the population is very heterogeneous in terms of income and the consumption insurance among agents are very imperfect, then imposing a representative agent model with linear tax schedule can potentially lead to misspecification error.

literally to be “correct”—in the sense that they are indeed the data generating mechanism--it is easier and arguably more appropriate to interpret the results based on HJ-distance. In that sense, the HJ-distance method is analogous to a “constrained model comparison” while the loglinear reduced form equation method is the “unconstrained” counterpart. Along this line we can provide an interpretation of the seemingly conflicting roles of housing in the reduced form approach and the HJ-distance approach that we find in the previous two sections. The positive role of housing in the reduced form equation approach indicates that, without the burden of structural restrictions, the inclusion of housing in the theoretical model is an improvement in the sense that composition risk arises as an important risk factor that helps price housing return. The negative role of housing in the HJ-distance approach implies, however, the way we introduce housing into the theoretical model may be too restrictive and calls for refinement. Thus, we see the two approaches as complementary as they pinpoint different aspects of the implications of a theoretical model.

(b) Why recursive utility model fits Hong Kong data well?

An interesting observation from the model ranking exercise is that the two recursive utility models (RUM) have salient advantage in explaining Hong Kong data. We discuss this result from the following perspectives.

Technically speaking, RUM provides a generalization of the standard expected utility model in which risk aversion and intertemporal elasticity of substitution (IES) are constrained to be reciprocal to each other implying that people are indifferent to the timing of resolution of uncertainty. By disentangling the tight link between risk aversion and IES, RUM makes possible the fluctuations in the long-run growth prospects of the economy and the time-varying level of economic uncertainty to drive asset prices, as has been demonstrated in the growing literature of long-run risks models (Bansal and Yaron, 2004; Hansen, Heaton and Li, 2008; Bansal, 2007, for survey). This literature has shown that RUM in conjunction with long-run risks is significantly better than the expected utility model in explaining asset market data and resolving various well-documented asset price anomalies and puzzles. A necessary condition for the long-run risks model to work is that people prefer early resolution of uncertainty (i.e. risk aversion larger than the reciprocal of IES) which is exactly what we find in our GMM structural estimation reported in Table 4.

How RUM works with long-run risks can be understood heuristically as follows. Recall that in the expected utility CCAPM and its variants, including their housing-augmented versions, the Bellman equations are formulated in such a way that the current period utility is separable from the expectation of future utility. Thus, a revision of the expectation about the future will not have any direct effect on the marginal utility of consumption in the current period; it will affect the consumption-saving decision through an investment calculation. In the case of RUM, however, the Bellman equation is in a non-separable form. It means that, for instance, if there is a social or political event which leads to a revision of the expectation about the future, the current period marginal utility of consuming, say, an ice-cream cone, could become less (or more) tasty. It is true even when that event does not change the current period budget constraint. In that sense, the worries (or optimism) about the future would have a direct impact on the consumption decision today. Economic agent may be more (or less) willing to defer consumption and invest more today, which tends to drive up the risk premium of assets. Therefore, social events that are interpreted by the representative agent as a change in the long-run risk would affect the expected value of future utility and hence the asset prices.

It begs the question: what is the source of long-run risks in Hong Kong? As a small open economy that relies on international trade in goods and services, Hong Kong's long-run growth prospects can be easily influenced by changes in fundamentals originating from surrounding countries especially China. Political uncertainty is another major source of long-run risks in Hong Kong. Many studies support the view that political risk plays an important role in Hong Kong's asset market.[30] More recently, Chan (2006) argue that there are different levels of political risk pertaining to Hong Kong. First, since Hong Kong's return to China and the 1997 Asian Financial Crisis (which occur almost at the same time), there has been an increase in populism which may signal the demise of Hong Kong's traditional policy

[30] For instance, Chau (1997) argues that political risk is important in explaining house prices before 1994. Based on media coverage in the New York Times and the Wall Street Journal, Kim and Mei (2001) find that reports of political issues are closely related to "jump components" in the Hong Kong stock price index during 1989 to 1993.

of “big market, small government”—a fundamental change that is expected to adversely affect Hong Kong’s long-term growth. In addition, the political institutions in Hong Kong have not yet provided a platform acceptable to different social groups for a discussion for compromise.[31] As a result, tremendous tension has been brewing among different social groups and stakeholders, a long-run risk factor that rational investors are well aware of and naturally take into consideration. It is therefore hardly a surprise that a model like RUM capable of capturing such kind of risks will do well in explaining Hong Kong’s asset market data.

5. CONCLUSION

To assess the capacity for the consumption-based asset pricing models to simultaneously explain aggregate stock and housing returns in Hong Kong, we develop, estimate and compare eight variants of consumption-based asset pricing models with the asset market data from Hong Kong. They include the canonical CCAPM, Habit formation model and Recursive utility model; their Housing-augmented variants including HCCAPM, H-Habit formation model and H-Recursive utility model; Labor income model as well as Collateral constraint model.

Our empirical results are several folds. First, no model is rejected by the data. Thus, all consumption-based asset pricing models considered in this paper captures some important aspects of the asset return movements. On the other hand, to understand the most important driving force in the asset markets, we still need to assign some relative rankings on these models. We rank the models by two performance criteria: the average size of prediction errors from loglinear reduced form equation and the Hansen-Jagannathan (HJ) distance. Statistical significance of the model rankings is taken into consideration by classifying the models into a number of model confidence sets *a la* Hansen et al. (2011). In case of the reduced form equation comparison, we include several conventional metrics, such as AIC, BIC, MAE, MSE. We even incorporate the recently developed Mariano-Preve procedure to scientifically verify whether models with similar MAE and MSE figures.

[31] Among others, see Chan (2009), Bush (2014a, 2014b) for more discussion on this.

The following conclusions can be drawn from the model comparison exercise. (i) Composition risk (as captured by non-housing consumption share growth) is always relevant in explaining housing return but not necessarily so for stock return, suggesting that it is to a large extent an asset-specific risk factor. (ii) The *collateral constraint model* outperforms all other models in predicting housing return but otherwise only moderate in predicting stock return, whereas the *recursive utility model and its housing-augmented variant* are the best in stock return prediction and in HJ-distance comparison. This suggests that taking into account financial market imperfection should play an important role in modeling housing return, but its role may be secondary to a more realistic specification of agents' attitude towards risk and uncertainty in modeling stock return. (iii) Recursive utility model, with or without housing, has salient advantage in explaining Hong Kong's asset market data across different model comparison criteria. We interpret this as an example of the empirical success of the recursive utility cum long-run risk model (Bansal and Yaron, 2004), in view of the prevalence of external fundamental shocks and political risks in Hong Kong. (iv) Adding labor income risk on top of the standard consumption growth and composition risks yields *no improvement*, for both asset returns and across model comparison criteria.

Clearly, future research can be extended in different directions. First, the analysis can be carried out with data from other Asian cities. We can also consider models with wealth-varying elasticities of intertemporal substitution, more heterogeneity among agents and how we can account for the intra-city variations of house prices, the time series movements in the asset markets with the economy.[32]

[32] Among others, see Atkeson and Ogaki (1996), Guvenen (2006), Ogaki and Park (1997), Ogaki and Reinhart (1998).

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Table 1: A summary of various consumption-based asset pricing models

Models	Description
CCAPM	Representative-agent Lucas-tree model with time- and state-separable utility
HCCAPM	Housing-augmented two-good version of CCAPM
Habit Formation model	CCAPM with external habit formation
H-Habit Formation model	HCCAPM with external habit formation
Recursive Utility model	CCAPM with Epstein-Zin-Weil recursive utility
H-Recursive Utility model	HCCAPM with Epstein-Zin-Weil recursive utility
Labor income model	Home production-augmented version of HCCAPM
Collateral constraint model	Heterogeneous-agent model with some agents subject to housing-collateral constraint

Table 2: Summary statistics (1983:1 – 2013:4)

Key variables	Mean	Std Error	Min	Max	1^{st} order autocorrelation
Stock return	1.0363	0.1418	0.5773	1.5247	-0.0868
Housing return	1.0299	0.0655	0.8349	1.2348	0.4334
Non-housing consumption share	0.7729	0.0391	0.7032	0.8302	0.9784
Consumption growth	1.0081	0.0195	0.9553	1.0797	0.0051
Wage growth	1.0072	0.0159	0.9557	1.0481	-0.2811
Inflation	1.0102	0.0148	0.9714	1.0393	0.3616
Short (3-month) interest rate	0.0001	0.0159	-0.0386	0.0411	0.3276
Long (10-year) interest rate	0.0052	0.0160	-0.0371	0.0444	0.3363

Notes: (i) All variables are measured in real terms (2010 constant price). (ii) The two asset returns, consumption growth, wage growth and inflation are measured in gross rate (= 1 + net rate) per quarter. (iii) The two interest rates are measured in net rate per quarter.

Table 3: Benchmark regression

	Stock Return		Housing Return	
	(1)	(2)	(3)	(4)
Constant	1.0119**	1.0152**	0.9754**	0.9744**
	(0.0338)	(0.0332)	(0.0156)	(0.0153)
GDP growth	0.1679	0.1094	0.6935**	0.7104**
	(0.3799)	(0.3651)	(0.1759)	(0.1689)
2008 crisis	-0.1791**	-0.1824**	-0.0416	-0.0407
	(0.0684)	(0.0679)	(0.0316)	(0.0314)
Short interest rate	-3.2616		-5.4189*	
(3-month)	(5.3613)		(2.4826)	
Long interest rate	3.7952		5.2654*	
(10-year)	(5.3310)		(2.4686)	
Yield curve slope		3.6323		5.3123*
(Long rate – short rate)		(5.3036)		(2.4529)
LR test		0.3618		0.1396
[p-value]		[0.5474]		[0.7085]
R^2	0.0877	0.0841	0.2321	0.2310
DW	2.1476	2.1437	1.2423	1.2008
Sample size	91	91	91	91

Notes: (i) Standard errors in parentheses. (ii) * 5% significant level; ** 1% significant level. (iii) Models 2 and 4 are restricted version of models 1 and 3 with the coefficients of short interest rate and long interest rate constrained to be the same but of opposite sign. The likelihood ratio (LR) tests indicate that the restricted models are not rejected at conventional significant level.

Table 4: Structural parameters

Models	Interpretation	Appear in:
β	Discount factor	All models
ρ	Double as relative risk aversion and inverse of elasticity of intertemporal substitution	CCAPM, HCCAPM, Habit, H-Habit, Labor income, and collateral constraint model.
	Inverse of elasticity of intertemporal substitution	Recursive utility and H-Recursive utility model
ϕ	Inverse of intratemporal elasticity of substitution of housing and non-housing consumption service	HCCAPM, H-Habit, H-Recursive utility, and Labor income model
σ	Relative risk aversion	Recursive utility and H-Recursive utility model
ν	Leisure share in utility function	Labor Income model
λ	Fraction of constrained households	Collateral constraint model
ω	Inverse of down payment to buy 1 unit of housing	Collateral constraint model
θ	Long-run inverse elasticity of housing demand	Collateral constraint model

Table 5: System GMM estimation of structural parameters

	CCAPM	HCCAPM	Habit Formation	H-Habit Formation	Recursive Utility	H-Recursive Utility	Labor Income	Collateral constraint model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β	0.9855** (0.0058)	0.9793** (0.0059)	0.9798** (0.0044)	0.9775** (0.0037)	1.0113** (0.0062)	1.0327** (0.0148)	0.9904** (0.0044)	
ρ	1.3977** (0.4394)	1.3965** (0.5264)	0.7561** (0.1748)	1.2618** (0.1671)	0.3512 (0.7253)	0.4941 (0.2569)	3.4582** (0.7437)	4.5087** (0.8849)
σ					1.2594** (0.2537)	1.4397** (0.1992)		
ϕ		0.9143** (0.1195)		0.8488** (0.0978)		-0.2749 (0.1893)	0.4468** (0.1538)	
ν							0.5098** (0.0849)	
λ								0.4784** (0.1320)
ω								-2.0749* (0.9814)
θ								-0.0502 (0.2344)
J-statistic [p-value]	16.27 [0.57]	18.22 [0.74]	16.26 [0.57]	18.18 [0.74]	11.92 [0.68]	15.66 [0.61]	18.12 [0.92]	23.61 [0.16]
Sample size	123	123	123	123	123	123	123	89
IV	t to t-2	t to t-2	t to t-2	t to t-2	t-1 to t-2	t-1 to t-2	t to t-2	t-1 to t-2

Notes: (i) Standard errors in parentheses. (ii) * 5% significant level; ** 1% significant level. (iii) Both stock and housing return equations are included in the GMM system. (iv) The instruments for models (1) – (7) include a constant, stock return, housing return, and variables appearing in the model's stochastic discount factor, with time indices indicated in row "IV". (v) The instruments for model (8) include a constant and up to two lags of all variables appearing in the two loglinear Euler equations.

Table 6: Loglinear reduced form regression for stock return

	CCAPM	HCCAPM	Habit	H-Habit	Recursive	H-Recursive	Labor Income	Collateral Constraint
Constant	0.0079 (0.0131)	0.0065 (0.0132)	0.0106 (0.0141)	0.0077 (0.0146)	-0.0225** (0.0045)	-0.0250** (0.0041)	0.0035 (0.0140)	0.0566 (0.0293)
Consumption	2.2868** (0.6328)	2.2879** (0.6327)	2.2895** (0.6346)	2.2759** (0.6397)	-1.0661** (0.2365)	-1.0955** (0.2125)	2.1344** (0.6738)	
Non-housing consumption share		1.1627 (1.1395)		0.9865 (1.2675)		1.8727** (0.3417)	1.3193 (1.1655)	
Lagged consumption			-0.3475 (0.6425)	-0.1623 (0.6876)				-1.3565* (0.5767)
Lagged Non-housing consumption share				0.3061 (1.1975)				
Wealth return					2.9659** (0.0948)	2.9936** (0.0853)		
Wage							0.5636 (0.8372)	
Lagged completions								0.0593 (0.0951)
Lagged interest rate (10-year)								-6.4821 (5.0817)
Lagged interest rate (3-month)								7.1095 (5.0997)
Housing price								0.4092 (0.2575)
Lagged housing price								-0.5991* (0.2530)
R^2	0.0966	0.1043	0.0988	0.1052	0.9004	0.9204	0.1077	0.1808
DW	2.2857	2.2806	2.2823	2.2875	1.9947	2.1148	2.2917	2.4519
Sample size	124	124	124	124	124	124	124	90

Notes: (i) Standard errors in parentheses. (ii) * 5% significant level; ** 1% significant level.

Table 7: Loglinear reduced form regression for housing return

	CCAPM	HCCAPM	Habit	H-Habit	Recursive	H-Recursive	Labor Income	Collateral Constraint
Constant	0.0153** (0.0055)	0.0181** (0.0050)	0.0073 (0.0056)	0.0125* (0.0053)	0.0109* (0.0053)	0.0139** (0.0048)	0.0194** (0.0052)	0.0220** (0.0067)
Consumption	1.5388** (0.2662)	1.5365** (0.2391)	1.5308** (0.2515)	1.5085** (0.2342)	1.0550** (0.2837)	1.0908** (0.2541)	1.6039** (0.2545)	
Non-housing consumption share		-2.3649** (0.4307)		-2.1491** (0.4641)		-2.2713** (0.4086)	-2.4336** (0.4402)	
Lagged consumption			1.0063** (0.2546)	0.6046* (0.2518)				-0.0712 (0.1323)
Lagged Non-housing consumption share				0.5461 (0.4384)				
Wealth return					0.4279** (0.1137)	0.3943** (0.1021)		
Wage							-0.2475 (0.3162)	
Lagged completions								0.0069 (0.0218)
Lagged interest rate (10-year)								0.3483 (1.1660)
Lagged interest rate (3-month)								-1.1515 (1.1701)
Housing price								1.0057** (0.0591)
Lagged housing price								-1.0548** (0.0581)
R^2	0.2150	0.3715	0.3047	0.4108	0.2972	0.4411	0.3747	0.8307
DW	1.2251	1.4201	1.3014	1.4425	1.4373	1.6493	1.4330	1.8063
Sample size	124	124	124	124	124	124	124	90

Notes: (i) Standard errors in parentheses. (ii) * 5% significant level; ** 1% significant level.

Table 8: Model comparison by (in-sample) prediction performance

Panel A: Stock return prediction				
	MSE × 10^2	MAE × 10^2	AIC	BIC
CCAPM	1.8173	9.8751	-3.9755	-3.9300
HCCAPM	1.8018	9.8865	-3.9680	-3.8997
Habit	1.8129	9.8626	-3.9618	-3.8936
H-Habit	1.8001	9.8990	-3.9366	-3.8229
Recursive utility	0.2001	3.4366	-6.1652	-6.0970
H-Recursive utility	0.1601	3.1276	-6.3725	-6.2815
Labor income	1.7951	9.8203	-3.9556	-3.8646
Collateral constraint	1.4180	8.9541	-4.1004	-3.9059
AR(1)	1.9893	10.4980	-3.8851	-3.8396
Panel B: Housing return prediction				
	MSE × 10^3	MAE × 10^2	AIC	BIC
CCAPM	3.2159	4.1514	-5.7074	-5.6619
HCCAPM	2.5746	3.9403	-5.9137	-5.8454
Habit	2.8484	3.9589	-5.8126	-5.7444
H-Habit	2.4135	3.7650	-5.9460	-5.8323
Recursive utility	2.8792	3.8570	-5.8018	-5.7336
H-Recursive utility	2.2896	3.7987	-6.0148	-5.9238
Labor income	2.5615	3.9504	-5.9026	-5.8117
Collateral constraint	0.7465	2.1729	-7.0445	-6.8501
AR(1)	3.3280	4.4327	-5.6731	-5.6276

Table 9: Mariano-Preve multiple (in-sample) forecast comparison

Panel A: Comparing stock return prediction performance based on MSE							
		All 9 models		Exclude model 1		Exclude model 1 - 2	
Model	MSE $\times 10^2$		χ^2 (df) [p-value]		χ^2 (df) [p-value]		χ^2 (df) [p-value]
1. H-Recursive	0.1601	Model 1-9	27.19 (8)	Model 2-9	26.05 (7)	Model 3-9	8.61 (6)
2. Recursive	0.2001		[6.52e-4]		[4.91e-4]		[0.196]
3. Collateral	1.4180	Model 1-8	27.02 (7)	Model 2-8	25.87 (6)	Model 3-8	6.11 (5)
4. Labor income	1.7951		[3.30e-4]		[2.34e-4]		[0.295]
5. H-Habit	1.8001	Model 1-7	27.01 (6)	Model 2-7	25.52 (5)	Model 3-7	5.18 (4)
6. HCCAPM	1.8018		[1.44e-4]		[1.10e-4]		[0.268]
7. Habit	1.8129	Model 1-6	26.34 (5)	Model 2-6	24.88 (4)	Model 3-6	5.10 (3)
8. CCAPM	1.8173		[0.76e-4]		[0.53e-4]		[0.164]
9. AR(1)	1.9893	Model 1-5	23.00 (4)	Model 2-5	21.22 (3)	Model 3-5	3.78 (2)
			[1.26e-4]		[0.94e-4]		[0.150]
		Model 1-4	22.33 (3)	Model 2-4	21.16 (2)	Model 3-4	2.02 (1)
			[0.55e-4]		[0.25e-4]		[0.154]
		Model 1-3	17.46 (2)	Model 2-3	14.45 (1)		
			[1.61e-4]		[1.43e-4]		
		Model 1-2	3.63 (1)				
			[0.0564]				

Panel B: Comparing stock return prediction performance based on MAE							
		All 9 models		Exclude model 1		Exclude model 1 - 2	
Model	MAE $\times 10^2$		χ^2 (df) [p-value]		χ^2 (df) [p-value]		χ^2 (df) [p-value]
1. H-Recursive	3.1276	Model 1-9	45.97 (8)	Model 2-9	44.93 (7)	Model 3-9	5.34 (6)
2. Recursive	3.4366		[2.4e-7]		[1.4e-7]		[0.499]
3. Collateral	8.9541	Model 1-8	45.36 (7)	Model 2-8	44.47 (6)	Model 3-8	2.02 (5)
4. Labor income	9.8203		[1.2e-7]		[0.6e-7]		[0.845]
5. Habit	9.8626	Model 1-7	40.42 (6)	Model 2-7	39.14 (5)	Model 3-7	1.60 (4)
6. CCAPM	9.8751		[3.8e-7]		[2.2e-7]		[0.808]
7. HCCAPM	9.8865	Model 1-6	40.26 (5)	Model 2-6	39.11 (4)	Model 3-6	1.06 (3)
8. H-Habit	9.8990		[1.3-7]		[0.7e-7]		[0.784]
9. AR(1)	10.4980	Model 1-5	39.91 (4)	Model 2-5	39.09 (3)	Model 3-5	1.04 (2)
			[0.4e-7]		[0.2e-7]		[0.591]
		Model 1-4	39.61 (3)	Model 2-4	38.91 (2)	Model 3-4	1.05 (1)
			[0.1e-7]		[0.0e-7]		[0.305]
		Model 1-3	34.32 (2)	Model 2-3	32.37 (1)		
			[0.4e-7]		[0.1e-7]		
		Model 1-2	2.88 (1)				
			[0.089]				

Table 9 (con't)

Panel C: Comparing housing return prediction performance based on MSE							
		All 9 models		Exclude model 1		Exclude model 1 - 3	
Model	MSE $\times 10^3$		χ^2 (df) [p-value]		χ^2 (df) [p-value]		χ^2 (df) [p-value]
1. Collateral	0.7465	Model 1-9	34.99 (8)	Model 2-9	14.15 (7)	Model 4-9	8.93 (5)
2. H-Recursive	2.2896		[2.68e-5]		[0.048]		[0.111]
3. H-Habit	2.4135	Model 1-8	31.91 (7)	Model 2-8	12.36 (6)	Model 4-8	6.18 (4)
4. Labor income	2.5615		[4.21e-5]		[0.054]		[0.185]
5. HCCAPM	2.5746	Model 1-7	30.12 (6)	Model 2-7	11.44 (5)	Model 4-7	2.19 (3)
6. Habit	2.8484		[3.72e-5]		[0.043]		[0.534]
7. Recursive	2.8792	Model 1-6	28.22 (5)	Model 2-6	11.42 (4)	Model 4-6	2.18 (2)
8. CCAPM	3.2159		[3.29e-5]		[0.022]		[0.335]
9. AR(1)	3.3280	Model 1-5	28.21 (4)	Model 2-5	7.58 (3)	Model 4-5	0.18 (1)
			[1.12e-5]		[0.055]		[0.669]
		Model 1-4	28.09 (3)	Model 2-4	7.16 (2)		
			[0.34e-5]		[0.027]		
		Model 1-3	27.77 (2)	Model 2-3	0.63 (1)		
			[0.09e-5]		[0.426]		
		Model 1-2	22.17 (1)				
			[0.24e-5]				

Panel D: Comparing housing return prediction performance based on MAE					
		All 9 models		Exclude model 1	
Model	MAE $\times 10^2$		χ^2 (df) [p-value]		χ^2 (df) [p-value]
1. Collateral	2.1729	Model 1-9	47.62 (8)	Model 2-9	11.04 (7)
2. H-Habit	3.7650		[0.12e-6]		[0.136]
3. H-Recursive	3.7987	Model 1-8	35.33 (7)	Model 2-8	8.69 (6)
4. Recursive	3.8570		[9.67e-6]		[0.191]
5. HCCAPM	3.9403	Model 1-7	35.25 (6)	Model 2-7	7.66 (5)
6. Labor income	3.9504		[3.85e-6]		[0.175]
7. Habit	3.9589	Model 1-6	33.52 (5)	Model 2-6	4.54 (4)
8. CCAPM	4.1514		[2.95e-6]		[0.337]
9. AR(1)	4.4327	Model 1-5	33.13 (4)	Model 2-5	4.21 (3)
			[1.12e-6]		[0.239]
		Model 1-4	32.91 (3)	Model 2-4	0.12 (2)
			[0.33e-6]		[0.939]
		Model 1-3	32.64 (2)	Model 2-3	0.04 (1)
			[0.08e-6]		[0.834]
		Model 1-2	32.11 (1)		
			[0.01e-6]		

Table 10: Hansen-Jagannathan (HJ) distance with Hansen-Lunde-Nason MCS procedure

		All 7 models		Exclude model 1-2	
Model	Sq. HJ $\times 10^3$		χ^2 (df) [p-value]		χ^2 (df) [p-value]
1. Recursive	0.0158	Model 1-7	26.40 (6)	Model 3-7	0.82 (4)
2. H-Recursive	0.3875		[1.87e-4]		[0.935]
3. CCAPM	1.6383	Model 1-6	24.79 (5)	Model 3-6	0.81 (3)
4. Habit	1.7827		[1.52e-4]		[0.846]
5. H-Habit	2.1687	Model 1-5	20.22 (4)	Model 3-5	0.30 (2)
6. Labor income	2.9191		[4.51e-4]		[0.860]
7. HCCAPM	3.1801	Model 1-4	19.22 (3)	Model 3-4	0.21 (1)
			[2.45e-4]		[0.641]
		Model 1-3	18.42 (2)		
			[0.99e-4]		
		Model 1-2	0.022 (1)		
			[0.879]		

Table 11: Ranking of models

Panel A: Stock return (in-sample) prediction	
Criteria	**Ranking of Models**
MSE	H-Recursive ≻ Recursive ≻ Collateral ≻ Labor Income ≻ HCCAPM ≻ H-Habit ≻ Habit ≻ CCAPM ≻ AR(1)
MSE with Mariano-Preve multiple forecast comparison	{H-Recursive, Recursive} ≻ {Collateral, Labor Income, HCCAPM, H-Habit, Habit, CCAPM, AR(1)}
MAE	H-Recursive ≻ Recursive ≻ Collateral ≻ Labor Income ≻ Habit ≻ CCAPM ≻ HCCAPM ≻ H-Habit ≻ AR(1)
MAE with Mariano-Preve multiple forecast comparison	{H-Recursive, Recursive} ≻ {Collateral, Labor Income, Habit, CCAPM, HCCAPM, H-Habit, AR(1)}
AIC	H-Recursive ≻ Recursive ≻ Collateral ≻ CCAPM ≻ HCCAPM ≻ Habit ≻ Labor income ≻ H-Habit ≻ AR(1)
BIC	H-Recursive ≻ Recursive ≻ CCAPM ≻ Collateral ≻ HCCAPM ≻ Habit ≻ Labor income ≻ AR(1) ≻ H-Habit
Panel B: Housing return (in-sample) prediction	
Criteria	**Ranking of Models**
MSE	Collateral ≻ H-Recursive ≻ H-Habit ≻ Labor income ≻ HCCAPM ≻ Habit ≻ Recursive ≻ CCAPM ≻ AR(1)
MSE with Mariano-Preve multiple forecast comparison	{Collateral} ≻ {H-Recursive, H-Habit} ≻ {Labor income, HCCAPM, Habit, Recursive, CCAPM, AR(1)}
MAE	Collateral ≻ H-Habit ≻ H-Recursive ≻ Recursive ≻ HCCAPM ≻ Labor income ≻ Habit ≻ CCAPM ≻ AR(1)
MAE with Mariano-Preve multiple forecast comparison	{Collateral} ≻ {H-Habit, H-Recursive, Recursive, HCCAPM, Labor income, Habit, CCAPM, AR(1)}
AIC	Collateral ≻ H-Recursive ≻ H-Habit ≻ HCCAPM ≻ Labor income ≻ Habit ≻ Recursive ≻ CCAPM ≻ AR(1)
BIC	Collateral ≻ H-Recursive ≻ HCCAPM ≻ H-Habit ≻ Labor income ≻ Habit ≻ Recursive ≻ CCAPM ≻ AR(1)
Panel C: Hansen-Jagannathan (HJ) distance	
Criteria	**Ranking of Models**
HJ	Recursive ≻ H-Recursive ≻ CCAPM ≻ Habit ≻ H-Habit ≻ Labor income ≻ HCCAPM
HJ with Hansen-Lunde-Nason MCS procedure	{Recursive, H-Recursive} ≻ {CCAPM, Habit, H-Habit, Labor income, HCCAPM}

Notes: (1) A ≻ B means A outperforms B. (2) {A, B} means A and B belong to the same model confidence set and their performance are indistinguishable.

Figure 1: Housing price and stock growth

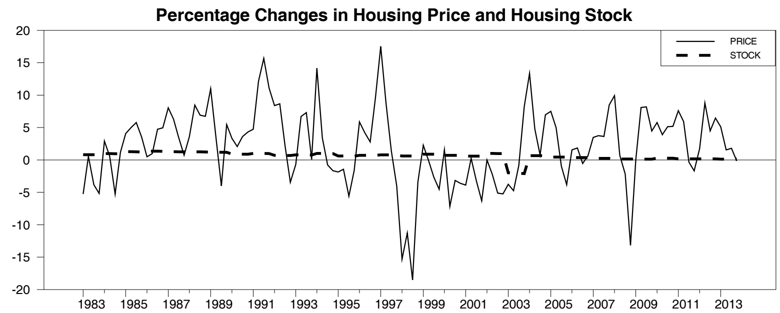

Figure 2: Stock and housing returns

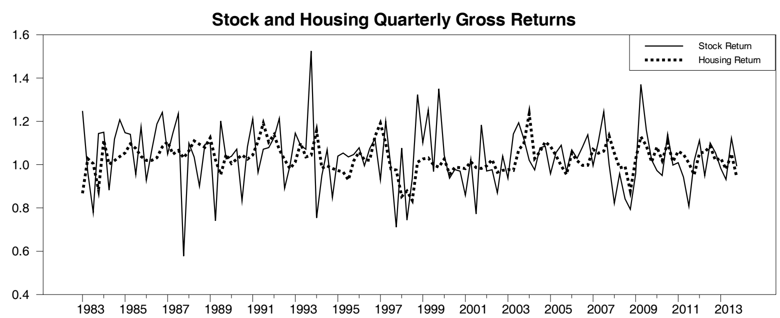

Figure 3: Stock returns absolute (in-sample) prediction errors

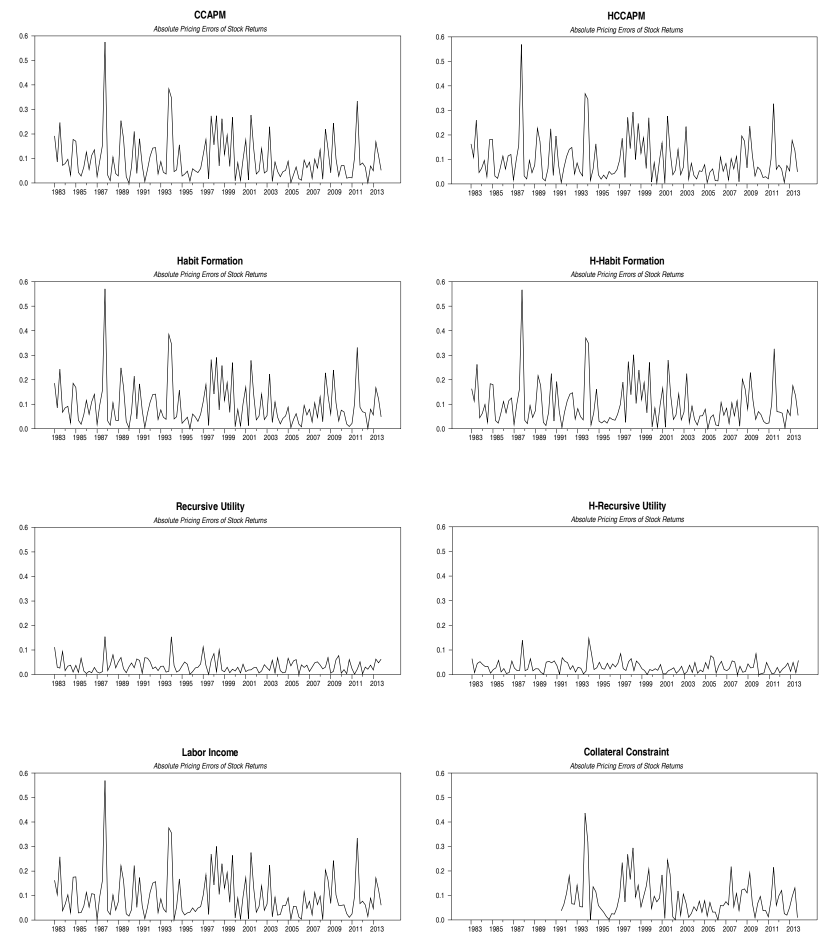

Figure 4: Housing returns absolute (in-sample) prediction errors