

Stock Price Dynamics of China: a Structural Estimation Approach*

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ABSTRACT

This paper develops and estimates several variants of consumption-based asset pricing models and compares their capacity in explaining the stock price dynamics of China. Our conclusions are: Adding housing to CCAPM and Habit formation models yields no significant benefit in predicting stock returns, but adding it to Recursive utility model does improve the prediction; Labor income model cannot help to reduce pricing error but Collateral constraint model outperforms almost all other models; some models cannot even defeat the simple autoregressive model in stock return prediction. Overall, H-Recursive Utility model has the best prediction performance. Directions for future research are discussed.

JEL classification: G10, E00, R30

Keywords: stock returns; housing-augmented consumption-based asset pricing; habit formation; recursive utility; labor income and home production; collateral constraint.

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I. INTRODUCTION

Is China different? Most authors and media would give an affirmative answer. Many articles and books have been written on the phenomenal economic growth in China. Figure 1 plots the real GDP of China, Germany, UK and US from 1999Q3 to 2012Q1, with starting values normalized to 100 to facilitate comparison. The plot confirms that China has indeed enjoyed a “growth decade” and her real GDP has effectively tripled during the sample period.

(Insert Figure 1 here)

On the other hand, there are dimensions along which China does not seem to be that different and, for a variety of reasons, they are often overlooked by the media. Stock price dynamics is one example. Figure 2 depicts the stock returns (measured by changes in stock market index) of the same set of countries for the same sample period as Figure 1. We again normalize the starting values to 100 across countries to facilitate comparison. Interestingly, the behavior of stock returns across countries looks a lot more similar than the corresponding real GDP figures. Table 1 further confirms that in terms of average return China is comparable to other countries. In terms of volatility (measured by standard deviation), it is very similar to the UK and is in between Germany and US. Moreover, the correlation between the stock returns of US and China is higher than that between US and the other two European countries. It should be noticed that, officially speaking, China has not yet opened her capital account -- her currency is not internationally convertible and her stock market does not admit foreign investors except those with special permits. Somewhat surprisingly, despite the isolation of the Chinese stock market, the stock price dynamics in China appears to be comparable to those in more mature markets in the rest of the world.

(Insert Figure 2 and Table 1)

A natural question is: Do models that have been developed to explain asset prices in mature markets apply to China? In fact, as surveyed by Singleton (2006), most empirical tests of asset pricing models in the literature are based on more or less the same market portfolio data of US. It is unclear to what extent these models are applicable to other countries, notably the emerging markets and other developing regions. As one of the largest emerging market economies, China’s experience should provide valuable insight in answering this question. The Chinese asset price

data is also of interest in its own right. Due to her “Chinese style socialism”, China is a very special economic and political entity that provides a unique case among the emerging market economies. The Chinese government is heavily involved in the economy and yet market mechanism and individual incentives have been allowed to their fullest extent. In addition to directly running state-owned enterprises, both the central and regional governments also participate in the economy by being significant shareholders of many large private firms including, for example, the major banks, real estate developers, natural resource companies and utilities. It will therefore be interesting to examine the empirical performance of theoretical models originally conceived to explain asset price data in a conventional market economy when they are confronted with the corresponding data of the very special Chinese style market economy.

In this paper we will focus on the consumption-based capital asset pricing model (CCAPM) and its variants. A merit of this class of models is that it relates the asset market to the real economy through people’s optimal consumption-saving decisions. The model has a long history. The canonical theoretical framework is developed by Samuelson (1969), Lucas (1978), and Breeden (1979), among others. While the original model assumes time-separable utility function, it is soon enriched by additional features such as recursive preferences (Epstein and Zin, 1989, 1991; Weil, 1989a, 1989b) and habit formation (Abel, 1990; Campbell and Cochrane, 1999; Constantinides, 1990). Recently the model has been further extended in a number of directions. Piazzesi et al. (2005) introduce housing service consumption into the representative agent’s optimal consumption-saving problem. One implication is that non-housing consumption share now appears as an additional factor that predicts stock returns. In other directions various authors have introduced features such as housing collateral constraints (Lustig and Nieuwerburgh, 2004; Iacoviello, 2004), labor income, and home production (Ludvigson and Campbell, 2001; Santos and Veronesi, 2006; Davis and Martin, 2009) into the standard model, which in principle should improve the model performance in explaining asset prices.

In the light of these developments in the theoretical literature, we study the empirical performance of four groups of consumption-based asset pricing models: (1) The canonical CCAPM and its habit formation and recursive preferences variants; (2) The housing-augmented versions of CCAPM, habit formation and recursive preferences models; (3) The Davis and Martin (2009) variant of CCAPM with labor income, home production and housing; (4) An extension of

the Iacoviello (2004) heterogeneous agents collateral constraint model to include asset holding decisions. To the best of our knowledge, some of the housing-augmented models and the extended collateral constraint model that we derive in this paper have not appeared before. The development of these models contributes to the theoretical literature and hence will be of independent interest.

The model comparison exercise in this paper will contribute to our understanding of the financial market in China and the asset pricing literature in general. For instance, if the collateral constraint model outperforms the alternatives, it might suggest that the consideration of capital market imperfection will be important in understanding the stock price dynamics in China. On the other hand, if the labor income-home production model outperforms the others, it might suggest that the labor market exerts significant influence on the asset markets. Therefore, the model comparison exercise will enhance our understanding of the stock price dynamics itself, as well as its relationship with the real side of the economy.

In the asset pricing literature the relationship between the stock market and the macro economy has been well documented for mature markets (Asprem, 1989; Binswanger, 2004; Boyd and Levine, 2001; and Boucher, 2006, to name a few). And the topic has received increasing attention in emerging markets research recently. There is a growing literature focusing on the empirical relationship between stock price dynamics and macroeconomic factors in the emerging markets, for example, oil price (Cong et al., 2008; Basher and Sadorsky, 2006), monetary policy (Goodhart et al., 2003), exchange rate (Zhao, 2009), inflation (Wongbangpo and Sharma, 2002), industrial production (Basher and Sadorsky, 2006), consumption (Liu and Shu, 2004), GDP (Diebold and Yilmaz, 2008), and multiple macro factors such as Muradoglu et al. (2000), Wongbangpo and Sharma (2002), and Mukhopadhyay and Sarkar (2003). Regarding the research devoted specifically to China's stock price dynamics and macroeconomic factors, the existing literature tend to focus on reduced form estimation. For instance, using an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model and a lag-augmented VAR model, Wang (2010) find a bilateral relationship between inflation and stock prices in China, a unidirectional relationship between the interest rate and stock prices, but no significant relationship between GDP and stock prices. Hosseini et al. (2011) use a vector error correction model (VECM) to find that there are both long and short run linkages between crude oil price, money supply, industrial production, and inflation with stock prices in China and India. Bondt et

al. (2010) from the European central bank try to explain China's stock prices using conventional fundamentals (e.g. corporate earnings, risk-free interest rate, and a proxy for equity risk premium) via a modified version of the Campbell and Shiller (1988) dynamic present value model. They find that China's stock prices can be reasonably well explained by market fundamentals.

To complement the literature, to the best of our knowledge, our paper may be one of the first to explore the relationship between macroeconomic fundamentals and stock prices in China, based on GMM structural estimation of consumption-based and housing-augmented asset pricing models. Since most of the standard macroeconomic variables are in quarterly frequency, our paper naturally concentrates on lower frequency movements of the stock market. In addition, unlike stock market transactions, housing market transactions normally take much longer time to complete. Thus, focusing on lower frequency data would also allow us to use housing market information (such as housing expenditure) perhaps more sensibly. As argued by Singleton (2006), the structural estimation approach will enrich our understanding and enable a better interpretation of the empirical results in the light of equilibrium asset pricing theories. In particular, we will compare the estimates of certain preference parameters from different models. If the empirical estimates turn out to be similar, it will provide indirect evidence that these parameters are indeed structural and presumably policy-invariant which, for example, can be used for policy analysis.

With these considerations in mind, this paper aims to assess to what extent the various consumption-based asset pricing models and their housing-augmented variants can explain the stock price dynamics in China. More specifically, this paper tries to shed light on the following questions: First, whether adding housing to canonical asset pricing models can better explain stock price dynamics; Second, whether the consideration of the labor market and collateral constraints would improve the prediction of stock returns; Third, whether theory-based structural models can better predict stock returns, compared with a pure statistical model such as a simple AR model.

The structure of the paper is as follows. Section 2 briefly describes each of the structural models to be compared, with detailed derivations of various Euler equations relegated to a technical appendix. Section 3 reports the GMM structural estimation results. Section 4 explains the procedures for generating predicted returns from the structural models, reports the model comparison results, and interprets the empirical findings. Section 5 concludes and suggests directions for future research.

II. MODELS

In this paper, we will develop several variants of the consumption-based asset pricing models. Table 2a provides an overview and Table 2b highlights parameters that may appear in several different models. To fix the idea, it may be instructive to provide more details of all these models.

(Table 2a, 2b here)

In this section, we will outline the setup and the main equation(s) of each model, leaving the details in the appendix.

1. CCAPM:

Consider a representative agent who maximizes the life-long utility:

$$\max[E_0 \sum_{t=0}^{\infty} \beta^t U(C_t)] \quad (1)$$

Subject to: $C_t + p_t s_{t+1} = s_t(p_t + d_t)$, $p_t = p(d_t), d_t$.

where p_t is the stock price, C_t is the nondurable consumption and services, s_t is the number of stock shares and d_t is the dividend. In the appendix, we show that the Euler equation to be estimated is:

$$1 = E_t \left[\beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} (1 + R_{t+1}) \right] \quad (2)$$

where R_{t+1} is the asset return. In addition, the Arrow-Pratt measurement of the relative risk aversion (RRA) to consumption is:

$$RRA = -C_t \frac{U''(C_t)}{U'(C_t)} = \gamma \quad (3)$$

So under this kind of assumption of the utility function, we get the constant relative risk aversion (CRRA).

2. Housing CCAPM:

Following Piazzesi et al. (2003), a representative agent maximizes the following expected utility function in an exchange economy with two consumption goods: non-durable consumption c_t and housing service s_t :

$$E \left[\sum_{t=0}^{\infty} \left(\frac{\beta^t}{1-1/\sigma} \right) \left(c_t^{\frac{\varepsilon-1}{\varepsilon}} + \omega s_t^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}(1-1/\sigma)} \right] \quad (4)$$

Subject to the following budget constraint:

$$c_t + p_t^h h_t + p_t^s \theta_t = (p_t^s + d_t) \theta_{t-1} + p_t^h h_{t-1} \quad (5)$$

where h_t is the stock of housing capital, θ_t is the number of shares of “Lucas Tree” model, d_t is dividend, p_t^h is housing price, p_t^s is share price. Here, we assume $s_t = h_t$.

There are two preference parameters: (1) σ , which denotes the elasticity of intertemporal substitution; (2) ε , which denotes the elasticity of intratemporal substitution between housing and non-housing consumption. Also notice that, as the canonical CCAPM, the coefficient of relative risk aversion (RRA) is an inverse function of the elasticity of intertemporal substitution (EIS), $\gamma = 1/\sigma$.

In the appendix, we show that:

$$p_t^s = E_t[M_{t+1}(p_{t+1}^s + d_{t+1})] \quad (6)$$

$$p_t^h = E_t \left[M_{t+1} \left(p_{t+1}^h + \frac{u_2(c_t, s_t)}{u_1(c_t, s_t)} \right) \right] \quad (7)$$

where $M_{t+1} = \beta \left(\frac{c_{t+1}}{c_t} \right)^{\frac{1}{\sigma}} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{\varepsilon-\sigma}{\sigma(\varepsilon-1)}}$, $\alpha_t = \frac{c_t}{c_t + q_t s_t} = \left(1 + \omega \left(\frac{s_t}{c_t} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{-1}$

We notice that the pricing kernel now includes two parts: the first part is the same as canonical CCAPM, and the second part depends on changes in the share of non-housing consumption to total consumption expenditure. If utility over non-durable consumption and housing service is separable, $\sigma=\varepsilon$, the second term collapses to one, and consumption risk alone matters for asset pricing.

HCCAPM captures the idea of consumer’s intertemporal and intratemporal preference that the non-durable consumption is valued highly not only when consumption tomorrow is lower than today, but also when the relative consumption of housing services tomorrow is lower than today.

3. Habit Formation Model:

The habit formation model assumes that utility is affected not only by current consumption but

also by past consumption. It captures a fundamental characteristic of human behavior that repeated exposure to a stimulus diminishes the response to it. There are basically two forms of habit formation model in terms of the specification of the utility function: the “difference” form (Boldrin, Christiano and Fisher, 2001; Campbell and Cochrane, 1999; Constantinides, 1990, etc.) and the “ratio” form (Abel, 1990, 1999). In this paper, we only focus on the “external habit” model (called “catching up with the Joneses” by Abel, 1990, 1999) of “ratio” form.

Assume the representative agent’s utility function has the following form, which has a power function of the ratio C_t / X_t :

$$U_t = \sum_{j=0}^{\infty} \beta^j \frac{(C_{t+j} / X_{t+j})^{1-\gamma}}{1-\gamma} \quad (8)$$

X_t is the influence of past consumption levels on today’s utility. And in the appendix, we show that, under this kind of utility specification, the Euler Equation is:

$$1 = \beta E_t [(1 + R_{t+1})(C_t / C_{t-1})^{\kappa(\gamma-1)} (C_{t+1} / C_t)^{-\gamma}] \quad (9)$$

4. Housing-augmented Habit Formation Model:

The introduction of housing into the original habit formation model actually changes the form of the pricing kernel, so does the Euler equation. We can think of this model’s set-up as the combination of original habit formation one-good model with HCCAPM.

The representative agent maximizes the following lifelong utility:

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t / \overline{C_{t-1}}^{\kappa})^{1-1/\sigma}}{1-1/\sigma} \quad (10)$$

where

$$C_t = \left(c_t^{\frac{\varepsilon-1}{\varepsilon}} + \omega s_t^{\frac{\varepsilon-1}{\varepsilon}} \right) \quad (11)$$

Subject to:

$$c_t + p_t^h h_t + p_t^s \theta_t = (p_t^s + d_t) \theta_{t-1} + p_t^h h_{t-1} \quad (12)$$

Under this set-up, the pricing kernel for H-habit formation becomes:

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-1/\sigma} \left(\frac{C_t}{C_{t-1}} \right)^{(1/\sigma-1)\kappa} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{\varepsilon-\sigma}{\sigma(\varepsilon-1)}} \quad (13)$$

Where, $\alpha_t = \frac{c_t}{c_t + q_t s_t} = \left(1 + \omega \left(\frac{s_t}{c_t} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{-1}$

And the Euler Equations for stock and housing prices take the similar forms as of HCCAPM:

$$\begin{aligned} p_t^s &= E_t[M_{t+1}(p_{t+1}^s + d_{t+1})] \\ p_t^h &= E_t \left[M_{t+1} \left(p_{t+1}^h + \left(\frac{s_t}{c_t} \right)^{-1/\varepsilon} \right) \right] \end{aligned} \quad (14)$$

5. Recursive Utility model:

Mainly in order to cut the unrealistic relationship between relative risk aversion (RRA) and elasticity of intertemporal substitution (EIS) derived by the canonical CCAPM, Epstein and Zin (1989,1991) and Weil (1989) present a class of preference that they termed ‘‘Generalized Expected Utility’’(GEU) which allows independent parameterization for RRA and EIS.

The representative consumer-investor’s problem is as follows:

$$Max U_t(C_t, E_t U_{t+1}) = [(1 - \beta)C_t^\rho + \beta(E_t U_{t+1}^\alpha)^{\rho/\alpha}]^{1/\rho} \quad (15)$$

Subject to:

$$\forall t, W_{t+1} = I_t \left[R_{1,t} + \sum_{j=2}^N \varpi_{j,t} (R_{j,t+1} - R_{1,t}) \right]$$

This is the so-called ‘‘Epstein-Zin-Weil’’ utility. In this recursive preference set up, the coefficient of relative risk aversion $\gamma = 1 - \alpha$ while the elasticity of intertemporal substitution (EIS) is $\sigma = 1 / (1 - \rho)$. It disconnects the reciprocity relationship between RRA and EIS which is indeed the case in the canonical model. And we can see that when $\alpha = \rho$, the recursive preference model reduced to the canonical situation.

The appendix shows the steps that we derive the Euler Equation:

$$1 = E_t \left\{ \left[\beta^{\alpha/\rho} \left(\frac{C_{t+1}}{C_t} \right)^{\alpha - \alpha/\rho} (1 + R_{w,t+1})^{\alpha/\rho - 1} (1 + R_{i,t+1}) \right] \right\} \quad (16)$$

6. Housing-augmented Recursive utility model:

As in the case of the H-Habit formation model, incorporating housing into the original recursive utility model will change the form of the pricing kernel as well as the Euler Equation. Based on the set up of recursive utility model and HCCAPM, the representative consumer’s problem is as follows:

$$Max U_t(C_t, E_t U_{t+1}) = [(1 - \beta)C_t^\rho + \beta(E_t U_{t+1}^\alpha)^{\rho/\alpha}]^{1/\rho} \quad (17)$$

$$\text{Subject to: } \forall t, W_{t+1} = I_t \left[R_{1,t} + \sum_{j=2}^N \varpi_{j,t} (R_{j,t+1} - R_{1,t}) \right]$$

$$\text{where } C_t = g(c_t, s_t) = \left(c_t^{\frac{\varepsilon-1}{\varepsilon}} + \omega s_t^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

After some algebraic manipulation, the pricing kernel in this problem becomes:

$$M_{t+1} = \beta^{\alpha/\rho} \left(\frac{c_{t+1}}{c_t} \right)^{\alpha-\alpha/\rho} (1 + R_{w,t+1})^{\alpha/\rho-1} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{-\rho+\alpha\varepsilon(1-\rho)}{(\varepsilon-1)\rho}} \quad (18)$$

And the Euler equations for pricing stock and housing take the similar form of HCCAPM. More details are provided in the appendix.

7. Labor Income model:

We adopt the labor income model set-up by Davis and Martin (2009). In the model, the representative agent value market consumption (which is also the numeraire) and a home consumption good that is produced from the stock of housing, home labor, and a labor-augmenting technology shock. A merit of this model is that it incorporates the “household production” idea of Becker (1976) into the traditional asset pricing models, and gives a role for the market wage to influence the marginal utility of housing service through the home consumption.

More specifically, the agent solves the following maximization problem:

$$\max_{\{c_{m,t}, l_{m,t}, k_{h,t}, A_{t+1}, K_{h,t+1}\}_{s=0}^{\infty}} \sum_{s=0}^{\infty} \beta^s E_t(U_{t+s}) \quad (19)$$

Subject to:

$$0 \geq \sum_{i=1}^N A_{i,t} R_{i,t} + (r_t + p_t) K_{h,t} + w_t l_{m,t} - c_{m,t} - r_t k_{h,t} - \sum_{i=1}^N A_{i,t+1} - p_t K_{h,t+1} \quad (20)$$

In this set-up, $R_{i,t}$ is gross stock return, $K_{h,t}$ is home capital-the house, $l_{m,t}$ is the time spent at working at the market; p_t is the price of the house; r_t is the rent of house. The utility function is based on the combination of market (numeraire) consumption and home consumption, denoted \hat{c}_t , leisure is n_t^v :

$$u_t = \frac{(\hat{c}_t n_t^v)^{1-\sigma}}{1-\sigma}$$

where $\hat{c}_t = [(1-\gamma)c_{m,t}^\rho + \gamma c_{h,t}^\rho]^{1/\rho}$, ($\rho \neq 1$); $\hat{c}_t = c_{m,t}^{1-\gamma} c_{h,t}^\gamma$ ($\rho = 0$).

The consumption aggregate is CES combination of market consumption $c_{m,t}$ and home consumption $c_{h,t}$; And we assume $c_{h,t} = k_{h,t}$, which means home consumption is equal to the home capital; $n_t = 1 - l_{m,t}$, leisure is defined as 1 (the normalized amount) minus time spent working at market;

The FOC of this problem can be derived as follows, which will be used as the moment conditions for GMM estimations (more details are provided in the appendix):

$$0 = 1 - \beta E_t \left(\frac{\lambda_{t+1}}{\lambda_t} R_{i,t+1} \right) \quad (21)$$

$$0 = 1 - \beta E_t \left(\frac{\lambda_{t+1}}{\lambda_t} R_{h,t+1} \right) \quad (22)$$

$$0 = \frac{c_{m,t}}{w_t n_t} - \left(\frac{1-\gamma}{\nu} \right) \left(\frac{c_{m,t}}{\hat{c}_t} \right)^\rho \quad (23)$$

$$0 = x_t - \left(\frac{\gamma}{1-\gamma} \right) \left(\frac{k_{h,t}}{c_{m,t}} \right)^\rho \quad (24)$$

8. Collateral Constraint Model:

Iacovello (2004) developed this two-agent, dynamic general equilibrium model in which home (collateral) values affect debt capacity and consumption possibilities for a fraction of the households. It considers the situation where the borrowing capacity of indebted households is tied to the value of their home, house prices should enter a correctly specified aggregate Euler equation for consumption. We modified Iacovello's set-up by adding stock trading into the representative agent's behavior and derive the asset pricing formula under this set-up.

For non-constrained households, they maximize a standard lifetime utility function given by:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{(c_t^u)^{1-1/\sigma}}{1-1/\sigma} + j^u u(H_t^u) \right) \quad (25)$$

The budget constraint is:

$$C_t^u + Q_t(H_t^u - H_{t-1}^u) + R_{t-1}B_{t-1}^u + P_t^s \theta_t^u = B_t^u + Y_t^u + (P_t^s + d_t) \theta_{t-1}^u \quad (26)$$

The economy also has a fraction of constrained households, which assign a high weight to today's consumption and do not discount the future. The amount they can borrow cannot exceed a

fraction $m \leq 1$ of the next period's expected value of housing discounted by the rate of interest:

$$B_t^c \leq mE_t(Q_{t+1})H_t^c / R_t \quad (27)$$

And they maximize the following utility:

$$\max \ln c_t^c + j^c u(H_t^c) \quad (28)$$

subject to (27) and (26).

After solving the first order conditions and some algebraic manipulation, we can derive the aggregate consumption Euler equation for housing return prediction as follows:

$$E_t(c_t + \sigma(1-\lambda)(r_t + l_t) - \omega\lambda(q_t + r_t - E_t q_{t+1}) - \lambda q_t - \theta\lambda h_t) = 0 \quad (29)$$

where r stands for the short run risk free rate while l is long run risk free rate, q is the price of house and h is housing stock.

And the Euler equation for stock return prediction is as follows: (the derivation is detailed in the Appendix)

$$1 = E_t \left[\beta \left(\frac{C_{t+1}}{C_t} \right)^{\frac{-1}{(1-\lambda)\sigma}} \left(\frac{Q_{t+1} - R_{t+1}^{-1} m E_{t+1}(Q_{t+2})}{Q_t - R_t^{-1} m E_t(Q_{t+1})} \right)^{\frac{\lambda}{(1-\lambda)\sigma}} \left(\frac{u'(H_{t+1}^c)}{u'(H_t^c)} \right)^{\frac{-\lambda}{(1-\lambda)\sigma}} R_{t+1}^s \right] \quad (30)$$

III. EMPIRICAL ESTIMATION AND RESULTS:

In this section, we will first provide more details of the dataset we use, and then the estimation results we obtain.

1. The Data:

We use quarterly data for all variables and get them mainly from China Monthly Economic Indicators published by National Bureau of Statistics, PRC, China Population & Employment Statistics Yearbook as well as CEIC database. The time horizon for stock return prediction is from 1999Q3 to 2012Q1, based on data availability. The main variables that are used in the GMM estimation include: (1) Aggregate stock market return; (2) Real per capita consumption growth rate; (3) Non-housing consumption to total consumption ratio; (4) Aggregate wealth return constructed by the weighted average of aggregate stock return and labor income growth.

For aggregate stock return data, we get China Stock Return Index from CEIC and deflated

into real term by GDP deflator; for the real consumption growth data, we get the consumption expenditure per capita data from China Monthly Economic Indicators. Then we calculate the real consumption growth rate per capita by deflating the consumption growth rate by GDP deflator; for the data of non-housing consumption to total consumption share, it includes the calculation of quarterly total consumption expenditure per capita and housing service expenditure per capita. The per capita consumption data are discussed above. And for the housing service expenditure, we get its survey data from China Monthly Economic Indicators; for aggregate wealth return, we construct it by taking the weighted average of aggregate stock return and labor income growth, and the latter one is retrieved from China Population & Employment Statistics Yearbook. Some extra data needed in labor income model and collateral constraint model are described in the Appendix. Table 3 provides a summary statistics of the main variables discussed above.

(Insert Table 3 here)

2. Model estimation results:

Table 4 summarizes the estimation results for stock return, based on GMM. The moment conditions that we use to estimate the models are the first order conditions derived from each model, provided in the previous Section Two. We use Continuously Updated Weight matrix as the weighting matrix of GMM. For the instruments, in order to facilitate the model comparison, we fix and choose the same number of lags=2 (starting from t-1 onwards, namely, t-1 and t-2, in order to avoid the "time aggregation bias" addressed in Campbell and Mankiw (1989)) and the same set of main variables (i.e. the lags of consumption growth and aggregate stock return) as the instruments in each model. Moreover, we report over-identification J-statistics of the models: they are all insignificant at 5% level (except for labor income model), suggesting valid moment conditions, which indicate that the models are not rejected by the data generally. Most of the estimated parameters are significant at 5% level.

Moreover, we can see from the estimation results that for stock return predictions, models get economically reasonable parameter estimators: the estimated parameters actually belong to the intervals of parameter values suggested by the previously developed literature: for instance, the discount factors are all around 0.95 to 1.00, which is consistent with macro literature; the intertemporal elasticity of substitutions are all bigger than the intra-temporal elasticity of

substitutions, which is suggested by Piazzesi et. al. (2005) paper; the relative risk aversion values generally belongs to (0,10), which also matches the consumption-based asset pricing literature; finally, the specific parameters of labor income model and collateral constraint model are all consistent with the reasonable values suggested by the two related papers, respectively.

(Insert Table 4 here)

IV. MODEL COMPARISON

As we explained in the introduction, identifying the “best performing model” would actually help us to identify the “main driving force” of asset price. To implement comparison across models, we first set a benchmark case in which stock return is predicted based only on the information of itself, namely, the autoregressive AR (p) model. We provide the Bayes Information Criteria (BIC) and Akaike Information Criteria (AIC) for determining the order of the Autoregressive model in Table 5. As the econometrics theory indicates that in large samples, the AIC will overestimate p with nonzero probability, we rely on BIC to determine the reasonable lag length, which should be 1. Thus we choose AR(1) to be the benchmark model.

(Insert Table 5 here)

The model comparison method in this paper is to compare the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of each model, based on the comparison of model-generated aggregate stock return data and the observed return data. And we calculate model-generated stock return by log-linearizing the Euler Equation of asset pricing of each model.

More specifically, we proceed in the following steps:

- (1) Log-linearize the Euler Equation of asset pricing of each model.

Generally, under the assumptions of lognormality and conditional homoscedasticity:

$$E_t(M_{t+1}R_{t+1}^i) = 1 \quad (31)$$

This implies:

$$E_t m_{t+1} + E_t r_{t+1}^i + \frac{1}{2}(\sigma_m^2 + \sigma_i^2 + 2\sigma_{im}) = 0 \quad (32)$$

where $m_{t+1} = \ln(M_{t+1})$, $r_{t+1}^i = \ln(R_{t+1}^i)$; σ_m^2 and σ_i^2 are unconditional variances of m_t and r_t^i respectively; and σ_{im} is their unconditional covariance. After re-organizing terms:

$$E_t r_{t+1}^i = -E_t m_{t+1} - \frac{1}{2}(\sigma_m^2 + \sigma_i^2 + 2\sigma_{im}) \quad (33)$$

Observe that $E_t r_{t+1}^i$ is the one-step ahead forecast of the log-return of asset i . In other words, the loglinear Euler equation (33) can in principle generate theoretically motivated forecasts for log-return.

For example, in canonical CCAPM, the stochastic discount factor is $m_{t+1} = \ln(\beta) - \gamma d_{t+1}$, where $d_{t+1} = \ln(C_{t+1}) - \ln(C_t)$, and (33) becomes

$$E_t r_{t+1}^i = \delta + \gamma E_t d_{t+1}, \quad \delta = -\ln(\beta) - \frac{1}{2}(\sigma_m^2 + \sigma_i^2 + 2\sigma_{im}) \quad (34)$$

For other asset pricing models, the log-linear form of its Euler Equation can be found in the Appendix.

(2) In order to “give the model the best chance”, we use the observed consumption growth on the right-hand-side of (33) and choose δ to match the mean of log-return. This is equivalent to using de-mean data and computing forecast errors by:

$$e_{t+1} = \tilde{r}_{t+1}^i - \gamma \tilde{d}_{t+1} \quad (35)$$

where $\tilde{r}_{t+1}^i = r_{t+1}^i - \bar{r}$, $\tilde{d}_{t+1} = d_{t+1} - \bar{d}$. To produce the CCAPM graph of Figure 3, we plot r_{t+1}^i and $\bar{r} + \gamma \tilde{d}_{t+1}$.

(3) Sticking to the principle of “giving the model the best chance”, we choose the parameters to minimize forecast errors. We run loglinear regressions and the residuals give us the required log-return forecast errors.

For example, for canonical CCAPM, we simply run the loglinear regression:

$$r_{t+1}^i = \phi_0 + \phi_1 d_{t+1} + \varepsilon_{t+1} \quad (36)$$

and the least square residual will be:

$$\hat{\varepsilon}_{t+1} = r_{t+1}^i - \hat{\phi}_0 - \hat{\phi}_1 d_{t+1} = \tilde{r}_{t+1}^i - \gamma \tilde{d}_{t+1} \quad (37)$$

By definition of least square, $\sqrt{(1/T) \sum_i \hat{\varepsilon}_{t+1}^2}$ is the minimum RMSE.

(4) Calculate the RMSE and MAE based on the comparison of model-generated return and the actual data of return.

$$RMSE(i) = \sqrt{\frac{1}{N} \left(\sum_{j=1}^N (e^i)^2 \right)} \quad MAE(i) = \sqrt{\frac{1}{N} \left(\sum_{j=1}^N |e^i| \right)} \quad (38)$$

Clearly, RMSE tends to “punish” large forecasting error, while MAE tends to treat each error equally. In the Appendix , we provide an example to illustrate this point in details.

Our model comparison results are summarized in the Table 6.

(Insert Table 6 here)

We may notice that Housing-augmented models are always better than the non-Housing-augmented model. It may be just an illusion of the property of least squares, because the Housing-augmented model always has an additional regressor (i.e. the non-housing consumption share variable) than the non-Housing-augmented model. To solve this problem, we also calculate Bayes Information Criteria (BIC) and Akaike Information Criteria (AIC) model selection criteria which penalize large model size while reward small RMSE. It means that, only if BIC and AIC of model A is smaller than that of model B, conditional on RMSE of model A is smaller than that of model B, we can say that model A has better performance of forecasting than model B.

This table indicates that: (1) Adding housing to CCAPM and Habit formation models yields *no significant* benefit in predicting stock returns, but adding housing to Recursive utility model does improve the prediction; (2) Considering labor income and home production *cannot* reduce pricing error compared with previous models; (3) Considering Collateral Constraint can outperform all the consumption-based and housing-augmented models except for the Recursive utility and H-Recursive utility models; (4) The simple benchmark AR(1) model, which only employs the information of stock return itself, is outperformed by two models only—the Recursive utility model and H-Recursive model. The RMSE and MAE results ensure us that Recursive Utility and H-Recursive Utility model have satisfactory prediction ability, among the all.

Figure 3 shows the model-generated stock return with comparison to the actual stock return data:

(Insert Figure 3 here)

Finally, in order to display and analyze the pricing error structure in the time series sense, we

provide a series figures for models we compared. Basically, we plot the Absolute Pricing Error (which is defined as the absolute value of the forecast error) for each model across time and then give the economic explanation of China's economy for the periods which have comparatively large pricing error.

(Insert Figure 4 here)

Based on these figures, the characteristics of the trend of absolute pricing error are as follows:

First, for most models, the comparatively larger absolute pricing error cluster in the years of 2007 and 2008. In 2007, influenced by US subprime crisis, China's stock prices decreased a lot starting from August; In 2008, two social issues in real economy transmitted to stock market: one was the snow disasters in Southern China in January and the other was the massive earthquake in Wenchuan in May. Models which have large pricing error in these two years indicate that these macro asset pricing models cannot capture the stock price volatility due to the "rare disasters". Future research may therefore devote more efforts on modeling these "Rare Disasters" in the China's context. Second, compared with consumption-based and housing-augmented models, the labor income and collateral constraint models generate much less pricing error in year 2008, which means that these two models, considering home production and borrowing constraint in real estate credit market, have better ability in capturing "rare disasters" in the real economy fundamental. Third, the pricing error patterns are very similar for consumption-based models and their housing-augmented counterparts.

Table 8 summarizes the ranking of different models based on RMSE, MAE criteria respectively.

(Insert Table 8 here)

As we can observe from the table, the ranking in terms of MAE is not perfectly consistent as the RMSE case. The reason is that the parameters of the forecasting equations are chosen to minimize MSE. Thus, if we compare models in terms of RMSE, the ranking won't be contaminated by bad parameter choice. This is no longer the case if we compare models by MAE, because the parameters that minimize MSE may not minimize MAE. In other words, the inconsistent ranking in the MAE column is likely due to bad parameter choice.

Finally, we would like to measure whether the differences in model pricing errors are statistically significant. Following the literature, we employ the Diebold-Mariano Statistic (DM statistic thereafter) to compare the predictive accuracy for RMSE and MAE criteria. The accuracy of each forecast is measured by a particular loss function and we use two popular loss functions:

- (1) Square error loss and (2) Absolute error loss.

According to Diebold and Mariano (1995), under the null of equal predictive accuracy:

$$S \sim N(0,1)$$

Thus we can reject the null at 5% level if $|S| > 1.96$.

Table 9 reports the DM test results for the ranking of the models in predicting stock return according to RMSE and MAE criteria respectively. It compares the “best” model suggested by the RMSE and MAE criteria which is H-Recursive Utility with the alternative models, in a statistical sense. According to the DM test, our ranking of the models are mainly significant at 5% level, which means the “best model” indicated by our model comparison method is indeed producing less prediction error than the alternative models statistically. This shows that generally our model ranking is not because of measurement error.

(Insert Table 9 here)

8. CONCLUSION

In order to find a relevant model which can explain and predict aggregate stock return in China, we develop, estimate and compare four groups of macro asset pricing models by GMM using China’s asset market data: consumption-based models including canonical CCAPM, Habit Formation model and Recursive Utility model; housing-augmented consumption-based models including HCCAPM, H-Habit Formation model and H-Recursive Utility model; the model considering labor income and home production as well as collateral constraint model. To our knowledge, some of the housing-augmented models that we estimate have not appeared in any existing studies and we also heavily modify collateral constraint model in order to include stock trading behavior. Thus, the development of these models may also contain some independent interest for future research. We also compare these structural models with an AR(1) model which forecasts the stock return only based on the information of itself.

The previous development in macroeconomic asset pricing theory has mainly focused on the

financial market of US. Nevertheless, these models are not necessarily adapted to the specificities of areas outside US. Our results, to the best of our knowledge, is the first attempt to use structural estimation and systematically compare various macroeconomic asset pricing models in their abilities to account for the movements in the China's stock market.

Our empirical results indicate that: (1) These models, usually tested using US asset market returns, can fit China's asset return data well: based on GMM, the models are not generally rejected by the data; (2) For stock return prediction, adding housing into the consumption-based models can not universally outperform the original versions; (3) Incorporating labor income into the models does not improve model's performance; (4) Considering Collateral Constraint can outperform all the models except for the Recursive utility and H-Recursive utility models; (5) Only two models-Recursive Utility and H-Recursive Utility can "beat" the AR(1) model which forecasts stock return only based on the information of itself.

There are possible reasons why the consideration of housing market, labor market does not improve the prediction of stock return universally, compared with the consumption-based models. For instance, the discretionary government policy may be influential in the stock market and the current period stock price may be more efficient to reflect those "policy information" than the housing market, labor market, etc. Thus, statistically, an AR(1) model, which essentially use the current period stock price to predict the future ones, may outperform some structural models. Another possible reason of the failure of some of those structural models compared with AR(1) is due to the heterogeneity of agents in China: China is a large country with totally different economic and social environments across provinces, cities, regions, etc. Some agents may be constrained and not be able to participate the stock and housing market. Some agents may be more informed than the others. For instance, college-educated people who live in cities may have better access of information than the barely-educated peasants in rural area. They may have higher capacities to process the data as well. Thus, to account for the stock market of China, it may be important to take into consideration of the heterogeneity of economic agents, and hence it may be an important direction for further research.¹

¹ Among others, see Leung and Teo (2011) for related attempts.

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Table 1: Summary statistics of normalized stock returns

	China	Germany	UK	US
Mean	101.7043	94.2664	92.4372	100.5224
Standard Deviation	14.2989	22.5623	14.5240	6.2335
Correlation with US	0.4420	0.1279	0.2466	1
Autocorrelation	0.5887	0.9000	0.9142	0.4323

Table 2a: Models for comparison: A brief description

Models	Description
CCAPM	Canonical CCAPM for single good: consumption
H-CCAPM	Canonical CCAPM for two goods: consumption and house
Habit Formation	CCAPM with Habit Formation, for single good: consumption
H-Habit Formation	CCAPM with Habit Formation, for two goods: consumption and house
Recursive Utility	CCAPM with Recursive Utility, for single good: consumption
H-Recursive Utility	CCAPM with Recursive utility, for two goods: consumption and house
Labor Income Model	The asset pricing model containing labor income and house production
Collateral Model	The asset pricing model containing collateral constrain for borrowing

Table 2b: Parameter Descriptions of the models to be compared

Models	Interpretation	Appear in:
β	discount factor	All models
γ	relative risk aversion (RRA)	CCAPM, Habit Formation model
ε	intra-temporal elasticity of substitution (IAES)	HCCAPM, H-Habit Formation model, H-Recursive Utility model
σ	inter-temporal elasticity of substitution (IES)	HCCAPM, H-Habit Formation model, Labor Income model, Collateral model
α	1-RRA	Recursive Utility model, H-Recursive Utility model
ρ	1-1/IES	Recursive Utility model, H-Recursive Utility model, Labor Income model
ν	leisure share	Labor Income model
ξ	weight for home consumption	Labor Income model
s	1-1/IAES	Labor Income model
λ	consumption share for constrained household	Collateral model
m	inverse of downpayment to buy 1 unit housing	Collateral model
θ	long-run inverse elasticity of housing demand	Collateral model

Table 3: The summary statistics for the main variables

Key Variables	mean	s.d	max	Min
gross stock market return based on stock index of China	1.0204	0.1446	1.4331	0.7414
gross consumption growth rate per capita	1.0124	0.1105	1.2107	0.8078
gross non-housing share growth rate per capita	1.0001	0.0289	1.0586	0.9656
total wealth return based on weighted average of stock return and labor income	1.0219	0.1138	1.3537	0.7645

Table 4: GMM results for estimating stock returns

Notes: (1) Standard Errors are reported in the parentheses; P-values for the J-statistic are reported in the brackets; *: 10% significant level; **: 5% significant level; ***: 1% significant level. (2) The moment conditions we use are all based on the first order conditions derived from each model provided in Section 2. (3) The weighting matrix we used in GMM procedure is the Continuously Updated Weighting Matrix. (4) For the instruments, in order to facilitate the model comparison, we choose the same number of lags=2 (from t-1 onwards, namely, t-1 and t-2, in order to avoid "time aggregation bias" raised by Campbell and Mankiw (1989)) and the same set of main variables (i.e. the lags of consumption growth, aggregate stock return) as the instruments in each model.

	CCAPM	HCCAPM	Habit formation model	H-Habit Formation model	Recursive Utility model	H-Recursive Utility model	Labor Income Model	Collateral Model
β	0.9812*** (0.0189)	0.9834*** (0.0190)	0.9895*** (0.0190)	0.9947*** (0.0185)	0.9824*** (0.0221)	0.9835*** (0.0152)	1.1442*** (0.0111)	
γ	0.1572 (0.1938)	0.0291 (0.2546)	0.5545*** (0.1007)					
α					0.9171*** (0.6265)	1.1309*** (0.2795)		
ρ					1.0027** (0.4983)	0.9125*** (0.2835)		
ε		2.8402 (2.4868)		1.5170*** (0.3258)		1.7419** (0.9136)		
σ				2.1251*** (0.6547)			1.4773*** (0.0859)	0.6380 (0.9872)
ν							0.7228*** (0.0026)	
ξ							0.0495*** (0.0027)	
s							0.1233*** (0.0077)	
λ								0.1031 (0.7837)
m								0.9697*** (0.2878)
θ								-0.4452 (3.3804)
J-statistic	3.5730 [0.3114]	4.2649 [0.3713]	4.2776 [0.2330]	4.9366 [0.2939]	5.1368 [0.2735]	4.5921 [0.4677]	12.2677 [0.9516]	10.0691 [0.1217]

Table 5: Determining the Order of an Autoregressive Model

Lag(s)	BIC	AIC
1	-3.9495	-4.1661
2	-3.9477	-4.2726
3	-3.8506	-4.2838
4	-3.8582	-4.3997
5	-3.7543	-4.4041
6	-3.6888	-4.4469
7	-3.7019	-4.5683
8	-3.5969	-4.5717

Table 6: In-sample predictions on aggregate stock return under different model specifications

Model	RMSE	MAE	AIC	BIC
AR(1)	0.116	0.300	-4.234	-4.158
CCAPM	0.139	0.332	-3.875	-3.799
HCCAPM	0.138	0.333	-3.837	-3.723
Habit Formation model	0.134	0.326	-3.902	-3.788
H-Habit formation model	0.133	0.327	-3.868	-3.715
Recursive Utility model	0.110	0.299	-4.306	-4.192
H-Recursive utility model	0.104	0.294	-4.371	-4.220
Labor Income model	0.121	0.317	-4.067	-3.912
Collateral constraint model	0.109	0.298	-4.185	-3.953

Table 7: Ranking of models based on RMSE, MAE criteria for stock return prediction:

Criteria	Ranking of Models
RMSE	H-Recursive \succ Collateral Constraint \succ Recursive Utility \succ AR(1) \succ Labor Income Model \succ H-Habit \succ Habit Formation \succ HCCAPM \succ CCAPM
MAE	H-Recursive \succ Collateral Constraint \succ Recursive Utility \succ AR(1) \succ Labor Income Model \succ Habit Formation \succ H-Habit \succ CCAPM \succ HCCAPM

Table 8: The Diebold-Mariano (1995) Statistics for Comparing Predictive Accuracy

Notes: (1) The DM test is used to compare the forecasting ability for “the best model” indicated by RMSE and MAE criteria and the competing model; (2)* Significant at 10% level of significance. ** Significant at 5% level of significance. *** Significant at 1% level; (3) The significance sign indicates that our “best model” indeed produces less predictive error than the alternative model in statistical sense while the insignificant sign means our “best model” is not significantly better than the alternative model.

	For RMSE and MAE ranking, the best model is H-Recursive Utility model	
	MSE	MAE
CCAPM	-2.52363***	-2.20268***
HCCAPM	-2.59238***	-2.28234**
Habit model	-2.58058***	-2.41270***
H-Habit model	-2.73356***	-2.48385***
Recursive model	-1.18368	-0.76684
Labor income model	-1.99921**	-1.84372**
Collateral model	-0.72515	-0.36262
AR(1)	-0.63594	-0.49897

Figure 1: Real GDP comparison across countries:

Notes: The following figure illustrates relative real GDP change in four countries: China, Germany, US and UK.

The data sample is from 1999 Q3 to 2012 Q1. In order to display the relative changes, we re-normalized the real GDP data in the above four countries to 100 at the beginning of the period.

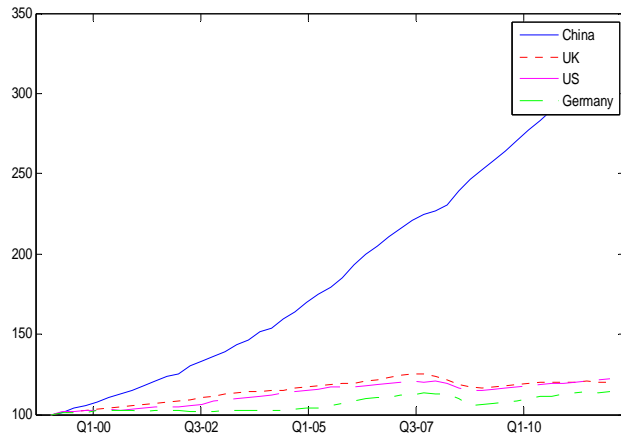


Figure 2: Stock price index comparison across countries:

Notes: The following figure illustrates relative stock price index change in four countries: China, Germany, US and UK. All the data are collected from the statistics of “Stock market: Share price index” provided by IMF. For China, the index is constructed based on Shanghai Stock Exchange and Shenzhen Stock Exchange, it is compiled using widely used method (Paasche weighted index); For Germany, the index is constructed based on DAX and CDAX price indices on the basis of the Laspeyres formula and are capital-weighted; For US, the index used is NYSE Composite Index which is a capitalization-weighted index that consists of all companies listed on the New York Stock Exchange (NYSE); For UK, the index constituent includes the FT30, FTSE 100, FTSE 250, FTSE 350, and FTSE Eurotrack 300 and 100.

The data sample is from 1999 Q3 to 2012 Q1. In order to display the relative changes, we re-normalized the stock price index in the above four countries to 100 at the beginning of the period.

We also use the plain index in each country to make the robustness check of this phenomenon. The results are provided in the Appendix.

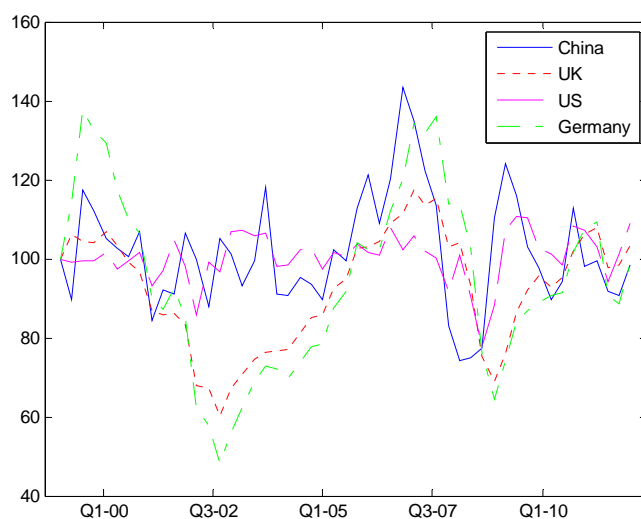
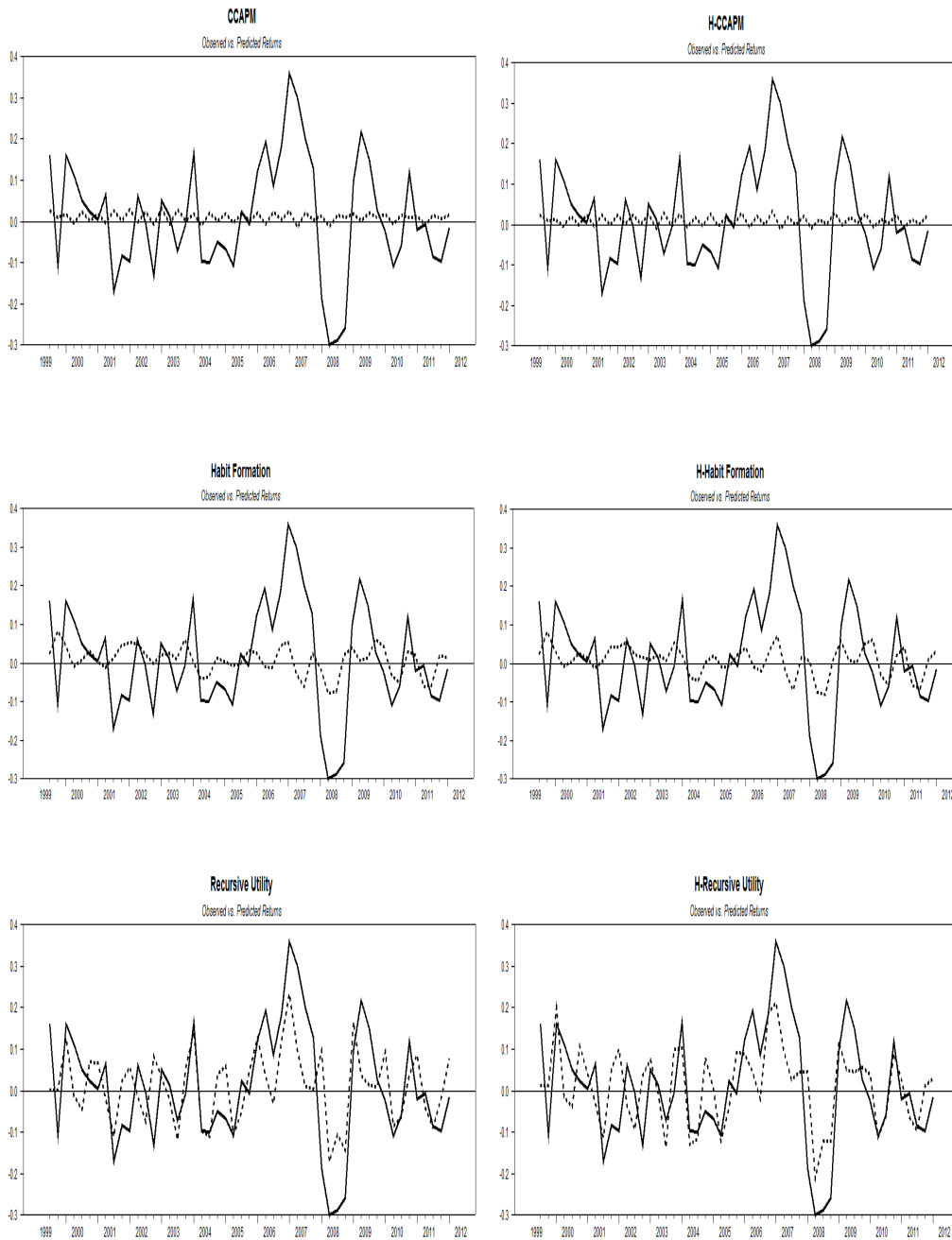


Figure 3: Stock return prediction:

Notes: Solid line= Observed stock log-returns; Dashed line= Predicted stock log-returns;



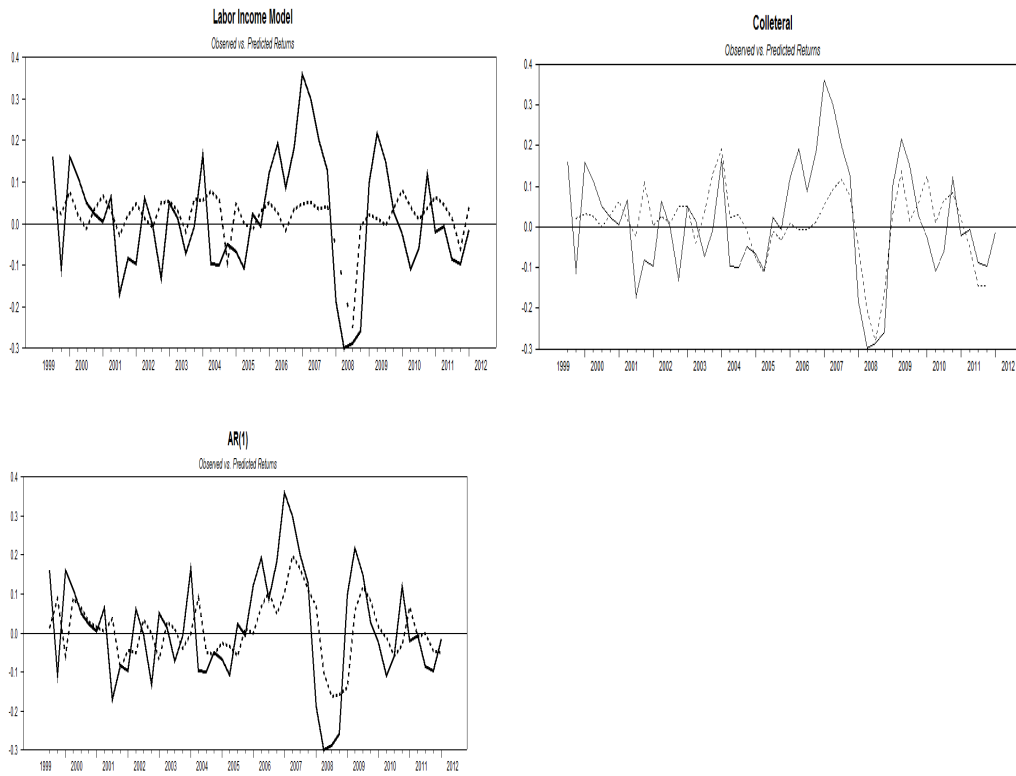


Figure 4: Time series dynamics of Absolute Pricing Error of the models

