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. We also compare these macro asset pricing models with a simple autoregressive model of stock return. Our conclusions are: Adding housing into the consumption-based models can not universally reduce pricing error for stock return prediction; considering labor income and collateral constraint respectively cannot improve model's performance in predicting stock return; and some macro models cannot even defeat the simple autoregressive model in stock return prediction. Directions for future research are discussed.

EFM classification: 310, 780

Key words: housing-augmented, consumption-based asset pricing, habit formation, recursive utility, labor income, collateral constraint

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Jinyue Dong will attend the meeting and present the paper; would like to be the discussant in the field of Asset Pricing (EFM code: 310)

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 provides a plot of the real GDP of China, Germany, UK and US from the period 1999 Q3 to 2012 Q1. To facilitate the comparison, we normalize the real GDP of all countries at the beginning of the sample, which is 1999Q3, as 100. Figure 1 confirms that China has enjoyed a “Growth Decade” and the aggregate real GDP has effectively tripled during the sampling period.

(Insert Figure 1 here)

On the other hand, there may be dimensions that China does not seem to be that different and for a variety of reasons, they have been overlooked by the media. Figure 2 shows the stock market indices of the same set of countries for the same sampling period as Figure 1. And to facilitate the comparison, we again normalize the starting point values to be 100 across countries. Interestingly, the graphs of these countries look a lot similar than the real GDP figure. Table 1 further confirms that in terms of mean, China is comparable to other countries. In terms of volatility (measured by standard deviation), it is very similar to the U.K. and is in between Germany and U.S. Moreover, the correlation between the U.S. stock index and the China stock index is higher than that between U.S. and Germany, or U.S. and U.K. It should be noticed that officially speaking, China has not opened her capital account. Her currency is not internationally convertible and her stock market does not allow foreign investors to participate except with some special permits. Yet, the stock market index of China seems to be comparable to the indices of other countries.[1]

(Insert Figure 2 and Table 1)

A natural question to ask will be: can models that have been developed to explain the asset prices of those developed countries may also apply to China? In fact, as surveyed by Singleton (2006), almost all the empirical tests are based on the same asset market portfolios data of US, thus the empirical performance of those models are unclear for other countries, such as the Emerging Market countries and some other developing regions. Since China is one of the largest

[1] In the appendix, we also provide robustness check for this phenomenon using the plain index of each country.

emerging market economies, China's experience may provide some lessons for other economies.

As a matter of fact, there may be additional justifications for more research efforts on the stock market price dynamics of China. Due to her "Chinese Style Socialism system", China is a very special economic and political entity among the emerging market economies. The Chinese government is heavily involved in the economy. State-owned enterprises play an important role in many sectors. Both the central and regional governments are significant shareholders of many "private firms", including the major banks, real estate developers, natural resource companies, utilities, etc. It is clearly in sharp contrast to the U.S. economy where the private sector dominates. It will therefore be interesting to examine the empirical performance of models designed to explain the U.S. market when they are confronted with the China data.

Clearly, there is a large literature of asset pricing models and it is beyond the scope of this paper to test all of them. We will focus on the Consumption-based Capital Asset Pricing Model (referred to canonical CCAPM hereafter) and its variants. A merit of this class of model is that it relates the asset market to the real economy through the optimal consumption-saving decisions. It has a long history. The canonical theoretical framework is developed by Samuelson (1969), Lucas (1978) and Breeden (1979), among others. It is then confronted with data by Mehra and Prescott (1985) and others. While the original model assumes time-separable utility function, it is soon enriched by additional features such as (1) Recursive Preference, proposed by Epstein and Zin (1989,1991) and Weil (1989a, 1989b); (2) Habit Formation, proposed by Abel (1990), Campbell and Cochrane (1999) and Constantinides (1990).

Recently, CCAPM has been further extended. For instance, housing is included in the utility function (for instance, see Piazzesi, Schneider and Tuzel, 2005), regarded as "Housing CCAPM" (HCCAPM hereafter). The idea is that the representative agent does not only concern the consumption volatility, but also the composition risk: the fluctuation in the relative share of housing service in their consumption basket. They show that the non-housing consumption share can be used to predict the stock return. Other authors introduce housing collateral constraint (among others, Lustig and Nieuwerburgh, 2004; Iacoviello, 2003) or labor income and home production (Ludvigson and Campbell, 2001; Santos and Veronesi, 2006; Davis and Martin, 2009, etc.) into the standard model, which seems to improve the model performance in predicting asset prices.

In light of these developments in the theoretical literature, we consider several variants of the consumption-based models in this paper. They 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 consumption-based models: HCCAPM, Housing-Habit formation model and Housing-Recursive utility model; (3) the model containing labor income and home production; (4) the collateral constraint model considering borrowing capacity of indebted households. To the best of our knowledge, some of the housing-augmented models that we estimate have not appeared in any existing studies. Thus, the development of these models may also contain some independent interest for future research.

On top of the theoretical models that we have described, as a model-neutral benchmark, we also estimate a simple autoregressive model of stock return, AR (p), where p is the number of lags in the model and will be chosen optimally by the data. If the "Efficient Market Hypothesis" (EMH) holds in its strong form, all relevant information have been reflected in the asset price itself and hence AR(p) would predict as good as other models. Clearly, given the special political and social structure of China, EMH may not hold. Thus, our comparison of the AR (p) model with other alternatives would provide an indirect test of the EMH in the context of China. In case EMH does not hold in the sampling period, it would highlight the value-added of the consumption and housing data and the structural estimation approach in the China context.

It should be noticed that the current paper may have some policy implications in China, on top of intellectual curiosity. For instance, if the "collateral model" outperforms the alternatives, it might suggest that the consideration of capital market imperfection is important in understanding the stock price dynamics. On the other hand, if the "labor income model" outperforms the others, it might suggest that the labor market exerts significant influence to the asset markets. Therefore, we consider the model comparison here may enhance our understanding of the stock price itself, as well as its relationship with the rest of the real economy.

In the Asset Pricing literature, the relationship between the stock market and macro economy has been well documented in the developed markets (Asprem, 1989; Binswanger, 2004; Boyd and Levine, 2001; Boucher, 2006; to name a few). And it has been received increasing attention in Emerging Markets research recently. There are a growing amount of literature that tries to find the relationship between stock price index and macroeconomic factors in the emerging markets. The macro factors that researchers investigate normally include oil price (Cong, Wei, Jiao, & Fan, 2008; Basher and Sadorsky, 2006), monetary policy (Goodhart, Mahadeva, and Spicer, 2003), exchange rate (Zhao, 2009), interest rate, inflation (Wongbangpo and Sharma, 2002), industrial production (Basher and Sadorsky's, 2006), consumption (Liu and Shu, 2004), GDP (Diebold, Yilmaz, 2008), etc., to name a few. And some researchers made a more comprehensive version to investigate most, if not all, of these macro factors altogether using emerging markets data, such as Muradoglu, Taskin and Bigan (2000), Wongbangpo and Sharma (2002), Mukhopadhyay and Sarkar (2003), etc.

Regarding the research of the relationship between China's stock price index and its macroeconomic factors, existing literature tend to focus on higher frequency data and reduced form estimation. The empirical results are mixed as well. For instance, Wang (2010) uses exponential generalized autoregressive conditional heteroskedasticity (EGARCH) and lag-augmented VAR (LA-VAR) models to find a bilateral relationship between inflation and stock prices, a unidirectional relationship between the interest rate and stock prices but no significant relationship regarding to real GDP. Hosseini, Ahmad and Lai (2011) use Johansen-Juselius (1990) Multivariate Cointegration and Vector Error Correction Model to find there are both long and short run linkages between crude oil price (COP), money supply (M2), industrial production (IP) and inflation rate (IR) with stock market index in China and India. Bondt, Peltonen and Santabarbara (2010) from European Central Bank empirically model China's stock prices using conventional fundamentals (corporate earnings, risk-free interest rate, and a proxy for equity risk premium) using a modified version of the dynamic present value model by Campbell and Shiller (1988) and find that China's stock prices can be reasonably well modeled using the fundamentals-based dynamic stock price model.

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 aggregate Chinese stock price, based on GMM structural estimation of consumption-based and housing-augmented asset pricing models. Since macro 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 take 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 surveyed by Singleton (2006), the structural estimation approach also enables us to interpret 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 are similar, it may provide indirect evidence that those parameters are indeed "deep parameters".

With these considerations in mind, this paper aims to assess to what extent the consumption-based and housing-augmented models can explain the stock price movements in China. More specifically, this paper tries to shed light on the following questions: First, whether the housing-augmented models outperform consumption-based models in explaining the stock price dynamics; Second, whether the consideration of the labor income market and collateral constraint would improve our prediction for the stock return; Third, whether the macroeconomic models can at least outperform the benchmark autoregressive model which is only based on the information of the stock return itself.

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 show the procedures and results for two criteria of model comparison and Section 5 concludes.

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)

1. CCAPM:

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

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

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

$p_t = p(d_t), d_t$ follows Markovian process.

(s_0, d_0) are given.

The Euler Equation derived from the above maximization problem indicates that current stock price is the expected discounted value of future price plus dividends:

$$P_t = E_t\left[\frac{\beta U'(C_{t+1})}{U'(C_t)}(P_{t+1} + D_{t+1})\right] \tag{2}$$

The term $\beta U'(C_{t+1}) / U'(C_t)$ is known as a stochastic discount factor or the intertemporal marginal rate of substitution of the consumer-investor.

Then consider the widely used power utility function form (Hansen and Singleton, 1982):

$$U(C_t) = \frac{1}{1-\gamma} C_t^{1-\gamma} \tag{3}$$

Under this assumption of the utility form, the stochastic discount factor now becomes:

$$M_{t+1} = \beta \frac{U'(C_{t+1})}{U'(C_t)} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \tag{4}$$

The Euler Equation thus has the form as:

$$1 = E_t\left[\beta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} (1 + R_{i,t+1})\right] \tag{5}$$

The Arrow-Pratt measurement of the relative risk aversion (RRA) to consumption is:

$$RRA = -C_t \frac{U''(C_t)}{U'(C_t)} = \gamma \tag{6}$$

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. (2007), 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 h_t:

$$E\left[\sum_{t=0}^{\infty}\left(\frac{\beta^t}{1-1/\sigma}\right)\left(c_t^{\frac{\varepsilon-1}{\varepsilon}} + \omega s_t^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}(1-1/\sigma)}\right] \tag{7}$$

Subject to the following budget constraint:

$$c_t + p_t^h h_t + p_t^s \theta_t = (p_t^s + d_t)\theta_{t-1} + p_t^h h_{t-1} \tag{8}$$

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), $\gamma = 1/\sigma$.

To solve for the above maximum problem, the Lagrangian method is used:

$$L = E\left[\sum_{t=0}^{\infty}\left(\frac{\beta^t}{1-1/\sigma}\right)\left(c_t^{\frac{\varepsilon-1}{\varepsilon}} + \omega s_t^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}(1-1/\sigma)} - \lambda_t(c_t + p_t{}^h h_t + p_t{}^s\theta_t - (p_t{}^s + d_t)\theta_{t-1} - p_t{}^h h_{t-1})\right] \tag{9}$$

The first order conditions are:

$$\partial L/\partial c_t = \beta^t(u_1(c_t, s_t) - \lambda_t) = 0 \tag{10}$$

$$\partial L/\partial h_t = \beta^t\{-\lambda_t p_t{}^h + \beta E_t(\lambda_{t+1} p_{t+1}{}^h) + u_2(c_t, s_t)\} = 0 \tag{11}$$

$$\partial L/\partial \theta_t = \beta^t\{-\lambda_t p_t{}^s + \beta E_t[\lambda_{t+1}(p_{t+1}{}^s + d_{t+1})]\} = 0 \tag{12}$$

These conditions can get the familiar asset pricing equations for housing return and stock return respectively as follows, except that the pricing kernel has different form from the canonical CCAPM:

$$p_t{}^s = E_t[M_{t+1}(p_{t+1}{}^s + d_{t+1})] \tag{13}$$

$$p_t{}^h = E_t\left[M_{t+1}\left(p_{t+1}{}^h + \frac{u_2(c_t, s_t)}{u_1(c_t, s_t)}\right)\right] \tag{14}$$

where,

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

We can 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 numeraire consumption and other consumption goods is separable, σ=ε, the second term collapses to one, and consumption risk alone matters for asset pricing.

In addition, it assumes that there exists an active rental market for housing, it can be shown that:

$$q_t = \frac{u_2(c_t, s_t)}{u_1(c_t, s_t)} = \omega\left(\frac{s_t}{c_t}\right)^{-\frac{1}{\varepsilon}} \tag{15}$$

Then α_t can be expressed as a share of non-housing consumption,

$$\alpha_t = \frac{c_t}{c_t + q_t s_t} = \left(1 + \omega\left(\frac{s_t}{c_t}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{-1} \tag{16}$$

HCCAPM captures the idea of consumer's intertemporal and intratemporal preference that the consumption numeraire 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 repeater 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 of habit formation model (Boldrin, Christiano and Fisher, 2001; Campbell and Cochrane, 1999; Constantinides, 1990, etc.) and the "ratio" form of habit formation model (Abel, 1990, 1999). In this paper, we only focus on the "external habit" (called "catching up with the Joneses" by Abel and Abel's, 1990, 1999) "ratio" form model.

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

$$U_t = \sum_{j=0}^{\infty} \beta^j \frac{(C_{t+j} / X_{t+j})^{1-\gamma}}{1-\gamma} \tag{17}$$

X_t is the influence of past consumption levels on today's utility. For the simplicity of the analysis and for the purpose to keep the model conditionally lognormal, specify X_t as an external habit depending on one lag of aggregate consumption:

$$X_t = (\overline{C}_{t-1})^{\kappa} \tag{18}$$

Where $\overline{C}_{t-1}$ is aggregate past consumption and the parameter kappa captures the degree of time non-separability. In the equilibrium, aggregate consumption equals the agent's own consumption, so in the equilibrium:

$$X_t = (C_{t-1})^{\kappa} \tag{19}$$

Under this kind of utility specification, the Euler Equation is:

$$1 = \beta E_t[(1+R_{i,t+1})(C_t / C_{t-1})^{\kappa(\gamma-1)}(C_{t+1}/C_t)^{-\gamma}] \tag{20}$$

Finally, in the empirical work, people usually set the parameter κ which governs the importance of the habit level as 0.9, 0.95 or 1.

4. Housing-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:

$$E_t \sum_{t=0}^{\infty} \beta^t \frac{(C_t / \overline{C_{t-1}}^{\kappa})^{1-1/\sigma}}{1-1/\sigma} \tag{21}$$

where

$$C_t = \left(c_t^{\frac{\varepsilon-1}{\varepsilon}} + \omega s_t^{\frac{\varepsilon-1}{\varepsilon}} \right) \tag{22}$$

Subject to:

$$c_t + p_t^h h_t + p_t^s \theta_t = (p_t^s + d_t)\theta_{t-1} + p_t^h h_{t-1} \tag{23}$$

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

$$M_{t+1} = \beta \frac{U'(C_{t+1}) g(c_{t+1}, s_{t+1})}{U'(C_t) g(c_t, s_t)} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-1/\sigma} \left(\frac{C_t}{C_{t-1}} \right)^{\kappa(1/\sigma-1)} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{\varepsilon-\sigma}{\sigma(\varepsilon-1)}} \tag{24}$$

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

And still the Euler Equations for stock and house price are as follows, but the form of pricing kernel is changed:

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

$$p_t^h = E_t\left[M_{t+1} \left(p_{t+1}^h + \frac{\partial U(C_t)/\partial C_t * \partial C_t / \partial s_t}{\partial U(C_t)/\partial C_t * \partial C_t / \partial c_t} \right) \right] = E_t\left[M_{t+1} \left(p_{t+1}^h + \left(\frac{s_t}{c_t} \right)^{-1/\varepsilon} \right) \right] \tag{25}$$

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 (1989a, 1989b) have presented a class of preference that they termed "Generalized Expected Utility"(GEU) which allows independent parameterization for RRA and EIS.

In this class of preferences utility is recursively defined by:

$$U_t = \left\{(1-\beta)C_t^{\rho} + \beta[E_t(U_{t+1}{}^{\alpha})]^{\rho/\alpha}\right\}^{1/\rho} \tag{26}$$

This is the so-called "Epstein- Zin-Weil" utility. In this recursive preference set up, the coefficient of relative risk aversion (RRA) γ is $1-\alpha$ (i.e. $\gamma = 1-\alpha$) while the elasticity of intertemporal substitution (EIS) is $\sigma = 1/(1-\rho)$. Although both RRA and EIS are constant, it cuts 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 representative consumer-investor's problem is as follows:

$$MaxU_t(C_t, E_tU_{t+1}) = [(1-\beta)C_t^{\rho} + \beta(E_tU_{t+1}{}^{\alpha})^{\rho/\alpha}]^{1/\rho} \tag{27}$$

Subject to:

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

The representative agent's intertemporal budget constraint evolves as the following:

$$W_{t+1} = (W_t - C_t)(1 + R_{w,t+1})$$

and they define the weight of the i^{th} asset in the portfolio as:

$$\varpi_{i,t} = Q_{i,t}P_i(z_t)/I_t,$$

where $I_t \equiv \sum_{i=1}^{N} Q_{i,t}P_i(z_t)$ and $1 = \sum_{i=1}^{N}\varpi_{j,t}$.

The stochastic discount factor (price kernel) indicated by the above maximization problem is:

$$M_{t+1} = \beta^{\alpha/\rho}\left(\frac{C_{t+1}}{C_t}\right)^{\alpha-\alpha/\rho}(1 + R_{w,t+1})^{\alpha/\rho-1} \tag{28}$$

Thus the Euler Equation is:

$$1 = E_t \left\{ [\beta^{\alpha/\rho} \left(\frac{C_{t+1}}{C_t} \right)^{\alpha - \alpha/\rho} (1 + R_{w,t+1})^{\alpha/\rho - 1} (1 + R_{i,t+1}) \right\} \tag{29}$$

Empirically, there are various ways to construct the variable R_w which represents the aggregate wealth return. For example, Epstein and Zin (1991) use the whole market portfolio return (such as the stock index) as the proxy for R_w. Some criticism against this approximation is that some other asset forms such as human capital, housing, etc. are not included in the stock index return, although they may correlated with stock index return to some degree. In our empirical work, we adopt the Campbell (1996)'s approximation that the aggregate wealth return is the weighted average of stock index return and human capital return, the latter one is approximated by labor income growth: $R_{w,t} = (1 - v) R_{a,t} + v R_{y,t}$. Following the empirical specification of Chen, Favilukis and Ludvigson (2008), we tried the weights as 0.333 and 0.667.

6. Housing-Recursive Utility model:

Very similar with the derivation process with H-habit formation model, incorporating house 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, the representative consumer's problem is as follows:

$$Max U_t (C_t, E_t U_{t+1}) = [(1 - \beta) C_t^{\rho} + \beta (E_t U_{t+1}{}^{\alpha})^{\rho/\alpha}]^{1/\rho} \tag{30}$$

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

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:

$$M_{t+1} = \beta \frac{U'(C_{t+1}) g_1(c_{t+1}, s_{t+1})}{U'(C_t) g_1(c_t, s_t)} = \beta^{\alpha/\rho} \left(\frac{c_{t+1}}{c_t} \right)^{\alpha - \alpha/\rho} (1 + R_{w,t+1})^{\alpha/\rho - 1} \left(\frac{\alpha_{t+1}}{\alpha_t} \right)^{\frac{-\rho + \alpha\varepsilon(1-\rho)}{(\varepsilon - 1)\rho}} \tag{31}$$

7. Labor Income model:

We adopt the labor income model set-up by Davis and Martin (2009). In the model, agents value market (numeraire) consumption and a home consumption good that is produced from the stock of housing, home labor, and a labor-augmenting technology shock. The purpose to introduce this model is to test whether it has better performance in estimating and predicting stock return than previous consumption-based models and housing-augmented models.

The representative agent solves the following maximization problem:

$$\max_{\{c_{m,t}, l_{m,t}, l_{h,t}, k_{h,t}, A_{i,t+1}, K_{h,t+1}\}} \sum_{s=0}^{\infty} \beta^s E_t(U_{t+s}) \tag{32}$$

Subject to:

$$0 \geq \sum_{i=1}^{N} A_{i,t} R_{i,t} + (r_t + p_t) K_{h,t} + w_t l_{m,t} - c_{m,t} - r_t k_{h,t} - \sum_{i=1}^{N} A_{i,t+1} - p_t K_{t+1,h} \tag{33}$$

In this set-up, R is gross stock return, K is home capital-the house, l is the time spent at working at the market; p is the price of the house; r 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 $\hat{c}_t = [(1-\gamma) c_{m,t}^{\;\rho} + \gamma c_{h,t}^{\;\rho}]^{1/\rho}, (\rho \neq 1)$.

The consumption aggregate is CES combination of numeraire 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 estimation:

$$0 = 1 - \beta E_t \left(\frac{\lambda_{t+1}}{\lambda_t} R_{i,t+1} \right) \tag{34}$$

$$0 = 1 - \beta E_t \left(\frac{\lambda_{t+1}}{\lambda_t} R_{h,t+1} \right) \tag{35}$$

$$0 = \frac{c_{m,t}}{w_t n_t} - \left(\frac{1-\gamma}{v}\right) \left(\frac{c_{m,t}}{\hat{c}_t} \right)^{\rho} \tag{36}$$

$$0 = x_t - \left(\frac{\gamma}{1-\gamma}\right) \left(\frac{k_{h,t}}{c_{m,t}} \right)^{\rho} \tag{37}$$

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 in which if 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 budget constraint.

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

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{(c_t^{\,u})^{1-1/\sigma}}{1-1/\sigma} + j^u u(H_t^{\,u}) \right) \tag{38}$$

The budget constraint is:

$$C_t^{\,u} + Q_t(H_t^{\,u} - H_{t-1}^{\,u}) + R_{t-1}B_{t-1}^{\,u} + P_t^s \theta_t = B_t^{\,u} + Y_t^u + (P_t^s + d_t)\theta_{t-1} \tag{39}$$

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⩽1 of the next period's expected value of housing discounted by the rate of interest:

$$B_t^{\,c} \le mE_t(Q_{t+1})H_t^{\,c} / R_t \tag{40}$$

And they maximize the following utility:

$$\max \ln c_t^{\,c} + j^c u(H_t^{\,c}) \tag{41}$$

subject to (39).

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

$$E_t(c_t + \sigma(1-\lambda)(r_t + l_t) - \omega\lambda(q_t + r_t - E_t q_{t+1}) - \lambda q_t - \theta\lambda h_t) = 0 \tag{42}$$

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 just the same as canonical asset pricing formula:

$$1 = E_t\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-1/\sigma}(1+R_{i,t+1})\right] \tag{43}$$

The empirical estimation by GMM is actually based on the Euler equation stated above and we can freely estimate the parameters correspondingly.

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; 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. We choose and report the best fitted result by varying the number of instrument variables (the lags of variables in the model) in each model. Moreover, we report over-identification J-statistics of the models: they are generally insignificant, suggesting valid moment conditions, which indicate that the models are not rejected by the data. 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 the 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 0.95-1.00 (except for the habit formation and collateral model which is around 1.01), 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)'s 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 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". 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 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)

Two kinds of model comparison methods are provided in this paper: the more conventional way, which is to compare the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE); and the more modern manner, which is to adopt the Hansen-Jagannathan (HJ) Distance method. The merits are clear. These methods capture different characteristics of the models. In addition, since many existing studies have applied the conventional method, adopting the conventional way here would facilitate the comparison with the literature. On the other hand, the HJ distance method is designed for GMM estimated rational expectation models and may capture some potential non-linearity in the data better. We consider the two methods complementary to each other, as some of the comparison method actually cannot apply to some specific model while some others can.

1. RMSE, MAE comparison:

We calculate the root mean square error (RMSE) and mean average error (MAE) for macro asset pricing models in the following process: suppose the target model is the true model for the data, substitute the GMM estimated parameter values into the Euler equation derived by the model; then to simulate the model-generated stock return using GMM estimators; finally, calculate the RMSE and MAE based on the comparison of model-generated returns and the actual data of returns. For specifically, we define the forecasting error of h-period ahead forecast from model *i* in the following manner,

$$\varepsilon^{i}_{t+h|t} = y_{t+h} - y^{i}_{t+h|t},$$

where y_{t+h} is the actual value of variable y in period (t+h), and $y^{i}_{t+h|t}$ is the prediction of model i on y_{t+h} based on the information up to period t. we check the model's average performance over many "episodes": in the first episode, the model uses data up to time T and then makes a 1-step ahead forecast of the T+1 value; in the second episode, the model uses data up to time T+1 and then makes a 1-step ahead forecast of T+2 value, etc. Finally, we rescale the average of these N squared forecast errors to calculate RMSE and MAE. Mathematically, it means that the RMSE and MAE generated by model i are simply

$$RMSE(i) = \sqrt{\frac{1}{N}\left(\sum_{j=1}^{N}\left(e^{i}_{T+j|T}\right)^{2}\right)},$$

$$MAE(i)=\sqrt{\frac{1}{N}\left(\sum_{j=1}^{N}\left|e^{i}{}_{T+j|T}\right|\right)}.$$

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 estimation results are summarized in the Table 6. This table indicates that (1) for stock return prediction, adding housing into the consumption-based models can not significantly reduce RMSE and MAE consistently; (2) considering labor income or home production cannot reduce pricing error compared with previous models; (3) compared with the benchmark AR(1) model, some macro models such as Recursive utility model, H-Recursive model, labor income model and collateral model, actually cannot outprform the AR(1) model which is only based on the information of stock return itself.

(Insert Table 6 here)

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 as follows. Basically, we plot the Absolute Pricing Error for each model across time and then give the economic explanation 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, Recursive utility model and H-Recursive utility model in general generate larger pricing error than other consumption-based and housing-augmented models, respectively especially in 2003 and the years following 2008. Third, collateral constraint model generally has larger pricing error than any other models. The "normal" error value of it is around 0.3 while for others it is around 0.15. The reason that the Collateral constraint model cannot explain China's stock price dynamics well is probably due to the apparent separation of stock and housing mortgage market in China.

2. Hansen-Jagannathan Distance (HJD) comparison:

Although comparing RMSE and MAE is available for all various forms of models, it has its drawbacks: it is designed for model comparison among linear models. Hence, it may not be able to capture the nonlinearities arise from rational expectation models, including the ones that we focus on. Thus, in this section, we provide apply HJD method for model comparison as well.

To appreciate the HJD method, we need to recall some practice in a typical GMM estimation. A GMM estimation of asset pricing model often requires a weighting matrix $\mathbf{W}_T$, that is different from the optimal weighting matrix $\mathbf{W}_T \neq \mathbf{S}^{-1}$. The reason is simple. The Hansen's J-test statistic depends on the model-specific matrix. Thus, Model 1 may "look better" simply because the Stochastic Discount Factors and pricing errors are more volatile than those of Model 2, not because its pricing errors are lower and its Euler equations less violated.

Hansen and Jagannathan (1997) solved this problem by the following way: to compare models using the following metric:

$$Dist_T(\boldsymbol{\theta}_j) \equiv \sqrt{\min_{\boldsymbol{\theta}} g_T(\boldsymbol{\theta}_j)' G_T^{-1} g_T(\boldsymbol{\theta}_j)} \tag{43}$$

where, $G_T \equiv \frac{1}{T}\sum_{t=1}^{T} \underbrace{R_t R_t'}_{N*N}$, $g_T(\boldsymbol{\theta}_j) \equiv \frac{1}{T}\sum_{t=1}^{T} \underbrace{[M_t(\boldsymbol{\theta}_j) R_t - 1_N]}_{N*1}$

This procedure can be achieved with GMM application, the only difference is that the weighting matrix is non-optimal with $\mathbf{W}_T \neq \mathbf{S}_T^{-1}$, which doesn't depend on the estimated parameters $\boldsymbol{\theta}_j$. Thus it is comparable across models. The HJ distance also provides a measure of misspecification: it gives least squares distance between the model's SDF and the nearest point to it in space of all SDFs that price assets correctly.

The metric *assumes all models are misspecified,* and provides method for comparing models by assessing which is the least misspecified. If Model 1 has a lower Distance than Model 2, we may conclude that the former has less specification error than the latter. This method can apply to all models except for the collateral model and AR(1) because they do not have basic form of asset pricing formula.

Table 7 reports the results of this method. We can see that the HJ distance results actually enhance the results based on RMSE and MAE stated above. For the stock return prediction, the housing-augmented consumption-based models can not generally reduce the HJ-distance, which means cannot produce less pricing error; and considering labor income and home production cannot significantly reduce the pricing error.

(Insert Table 7 here)

Table 8 summarizes the ranking of different models based on RMSE, MAE and HJ Distance criteria respectively. We can see from the two tables that although regarding our three questions concerned in this paper, HJ Distance result is generally consistent with that of RMSE and MAE results, the absolute ranking of all models is not that consistent between the two kinds of criteria. The possible reason for the difference is basically due to the different numerical calculation procedure and the measurement error of our variables.

(Insert Table 8 here)

Lastly, 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. As in the previous section, we use $\varepsilon^{i}_{t+h|t}$ to denote the prediction error of model *i* on period *(t+h)* value given period *t* information. The accuracy of each forecast is measured by a particular loss function and we use two popular loss functions:

(1) Square error loss: $L(\varepsilon^{i}_{t+h|t}) = (\varepsilon^{i}_{t+h|t})^2$

(2) Absolute error loss: $L(\varepsilon^{i}{}_{t+h|t}) = |\varepsilon^{i}{}_{t+h|t}|$

The null hypothesis of DM test is:

$$H_0 : E[L(\varepsilon^{1}{}_{t+h|t})] = E[L(\varepsilon^{2}{}_{t+h|t})]$$

And the alternative hypothesis is:

$$H_1 : E[L(\varepsilon^{1}{}_{t+h|t})] \neq E[L(\varepsilon^{2}{}_{t+h|t})]$$

The DM statistic is defined as:

$$S = \frac{\overline{d}}{(avar(\overline{d}))^{1/2}} = \frac{\overline{d}}{(LRV_{\overline{d}} / T)^{1/2}}$$

where:

$$\overline{d} = \frac{1}{T_0}\sum_{t=t_0}^{T} d_t \ , \ \ LRV_{\overline{d}} = \gamma_0 + 2\sum_{j=1}^{\infty}\gamma_j \ , \ \ \gamma_j = cov(d_t, d_{t-j})$$

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 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 our model ranking is not generally rejected by the data.

(Insert Table 9 here)

Ⅴ. 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. 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 and collateral constraint into the models do not improve model's performance neither; (4) Some of our macro models cannot even "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 and collateral constraint does not improve the prediction of stock return, 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.

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Table 1: Summary statistics of the normalized stock price indices

	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 U.S. stock price index	0.4420	0.1279	0.2466	1
Serial Correlation Coefficient	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	intratemporal elasticity of substitution (IAES)	HCCAPM, H-Habit Formation model, H-Recursive Utility model
σ	intertemporal 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
v	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
ω	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
rp (gross stock market return based on stock index of China)	1.0204	0.1446	1.4331	0.7414
cons (gross consumption growth rate per capita)	1.0124	0.1105	1.2107	0.8078
share(gross non-housing share growth rate per capita)	1.0001	0.0289	1.0586	0.9656
rw(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

	CCAPM	HCCAPM	Habit formation model	H-Habit Formation model	Recursive Utility model	H-Recursive Utility model	Labor Income Model	Collateral Model
β	0.9859** (0.0159)	0.9959*** (0.0227)	1.0031*** (0.0153)	0.9972*** (0.0166)	0.9925*** (0.0130)	0.9666*** (0.0327)	0.9902*** (0.0192)	1.0261*** (0.0130)
γ	-0.0470 (0.1837)		0.4714*** (0.0944)					
α					-0.2704 (0.6265)	2.1748*** (0.8729)		
ρ					0.1401 (0.2567)	2.6323 (1.6811)		
ε		0.9424*** (0.1873)		1.2508*** (0.2274)		1.6041*** (0.4712)		
σ		1.2331 (0.7855)		1.8467*** (0.5477)			1.3253*** (0.2445)	0.5179*** (0.0215)
v							0.0841*** (0.0121)	
ξ							0.2862*** (0.0150)	
s							-0.2043*** (0.0108)	
λ								1.6137*** (0.1347)
ω								-0.1201 (0.0891)
θ								-0.0072*** (0.0023)
J-statistic	10.6614 [0.1541]	8.5449 [0.2008]	10.6799 [0.1532]	15.9743 [0.1004]	5.0731 [0.0243]	4.0937 [0.2515]	21.8489 [0.0159]	34.2934 [0.1018]
IV_Lags	4	2	4	4	1	2	1	2

Foot notes: (1) Standard Errors are reported in the parentheses;

(2)P-values for the J-statistic are reported in the brackets;

(3)*: 10% significant level; **: 5% significant level; ***: 1% significant level

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 HK Stock Return under different model specifications

Model	RMSE	MAE
AR(1)	0.1477	0.1178
CCAPM	0.1439	0.1136
HCCAPM	0.1790	0.1389
Habit Formation model	**0.1399**	0.1142
H-Habit formation model	0.1445	**0.1135**
Recursive Utility model	0.1992	0.1720
H-Recursive utility model	0.2048	0.1628
Labor Income model	0.1927	0.1521
Collateral constraint model	0.2418	0.1977

Table 7: Model Comparison for stock return prediction: Hansen-Jagannathan Distance

Models	HJ-Distance
CCAPM	**3.8657e-011**
HCCAPM	2.9755e-006
Habit Formation	1.3010e-010
H-Habit Formation	3.5602e-006
Recursive Utility	2.5047e-005
H-Recursive Utility	7.5717e-007
Labor Income Model	1.2072e-004
Collateral Model	N.A.

Table 8: Ranking of models based on RMSE, MAE and HJ Distance criteria for stock return prediction:

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

Table 9: 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 based ranking, the best model is Habit formation model	
	MSE	MAE
CCAPM	-0.52238	-0.93539
HCCAPM	-2.92979***	-2.77860***
HHabit model	-0.66809	-0.90892
Recursive utility model	-2.77423***	-3.69758***
HRecursive model	-2.48322***	-2.68519***
Labor income model	-2.93685***	-2.74099***
Collateral model	-3.73633***	-4.54522***
AR(1)	0.96780	1.00742

	For MAE ranking, the best model is H-Habit formation model	
	MSE	MAE
CCAPM	0.10585	0.11940
HCCAPM	-2.03758 **	-1.83151 *
Habit formation model	0.66809	0.90892
Recursive utility model	-2.48816 ***	-3.34537 ***
HRecursive model	-2.42586 ***	-2.53559 ***
Labor income model	-3.46315 ***	-2.99278 ***
Collateral model	-4.03720 ***	-4.86534 ***
AR(1)	1.12816	1.28969

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.

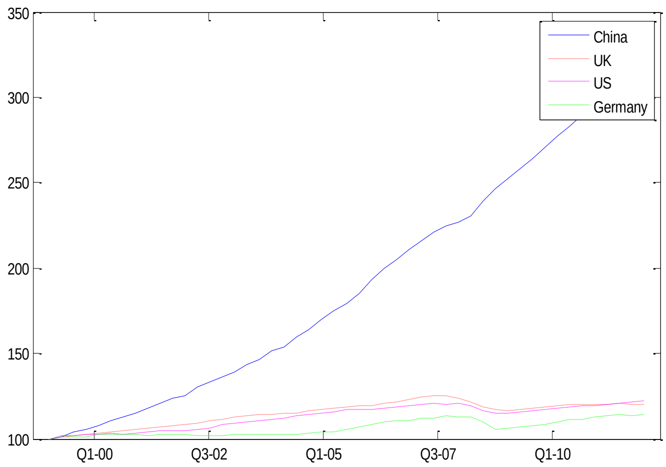


Figure 2: Stock price index comparison across countries:

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 Appendix 2.

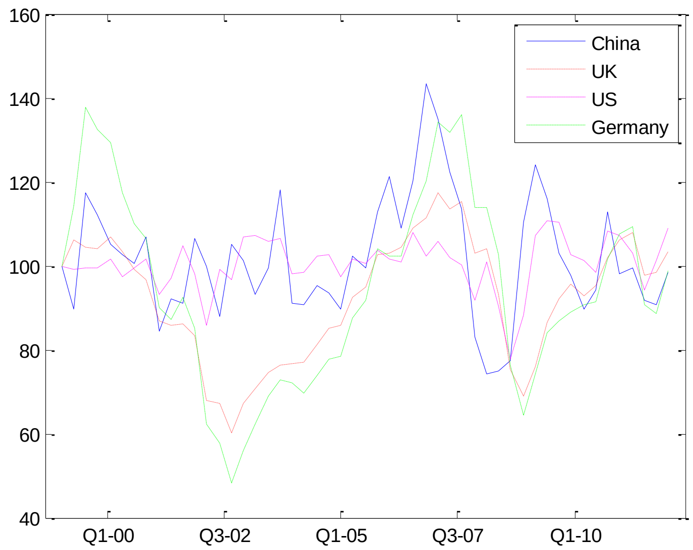


Figure 3: Stock return prediction:

Figure 3a: CCAPM:

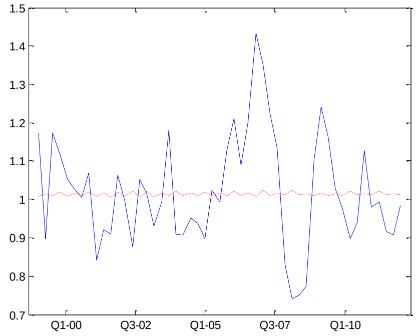


Figure 3b: HCCAPM:

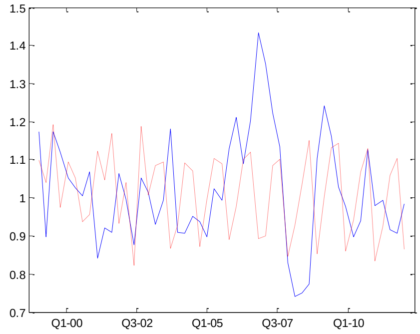


Figure 3c: Habit formation model:

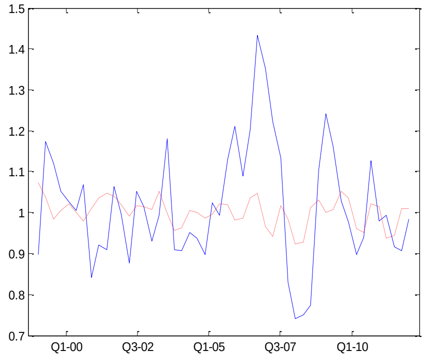


Figure 3d: H-Habit formation model:

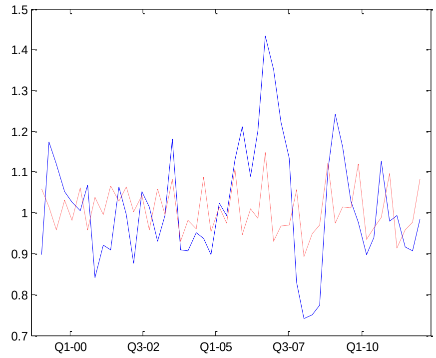


Figure 3e: Recursive Utility model

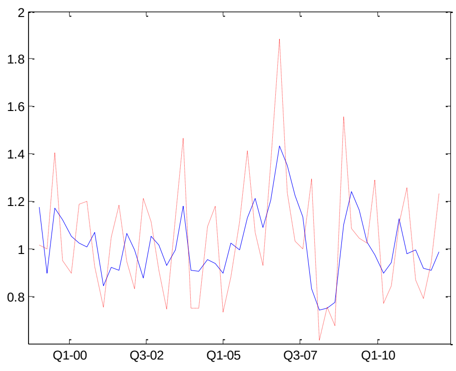


Figure 3f: H-Recursive Utility model

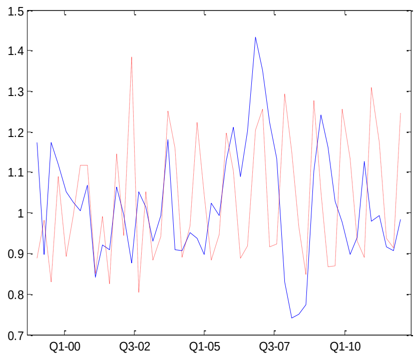


Figure 3g: Labor Income model:

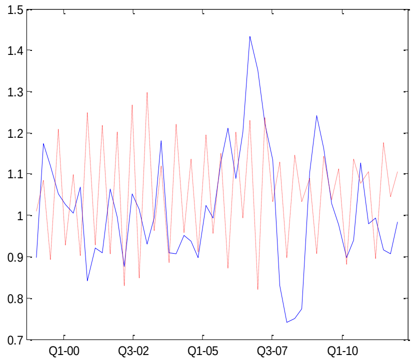


Figure 3h: Collateral Constraint model:

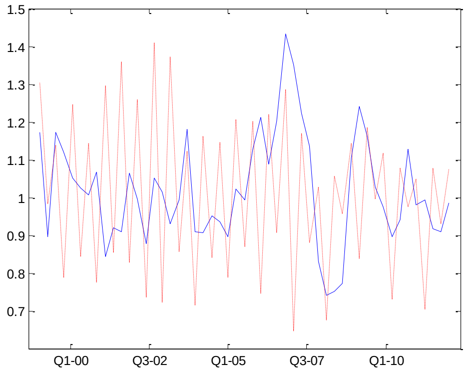


Figure 4: Time series dynamics of Absolute Pricing Error of the models

Figure 4a: CCAPM

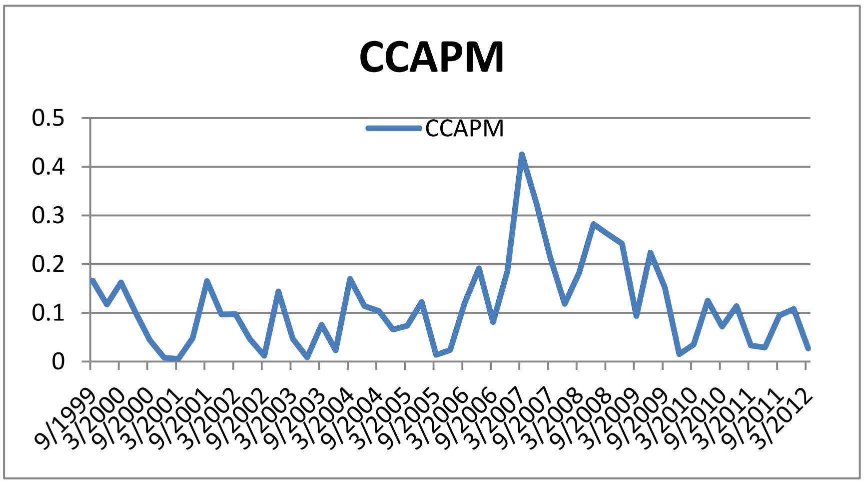


Figure 4b: Habit Formation model:

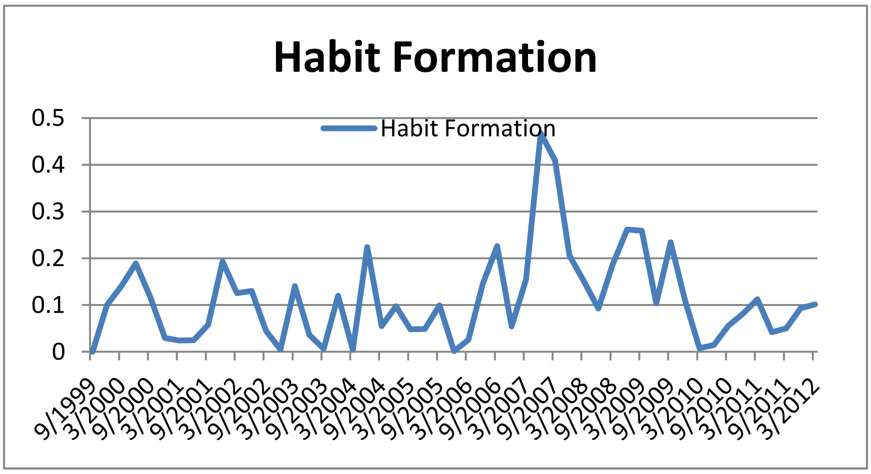


Figure 4c: Recursive utility model:

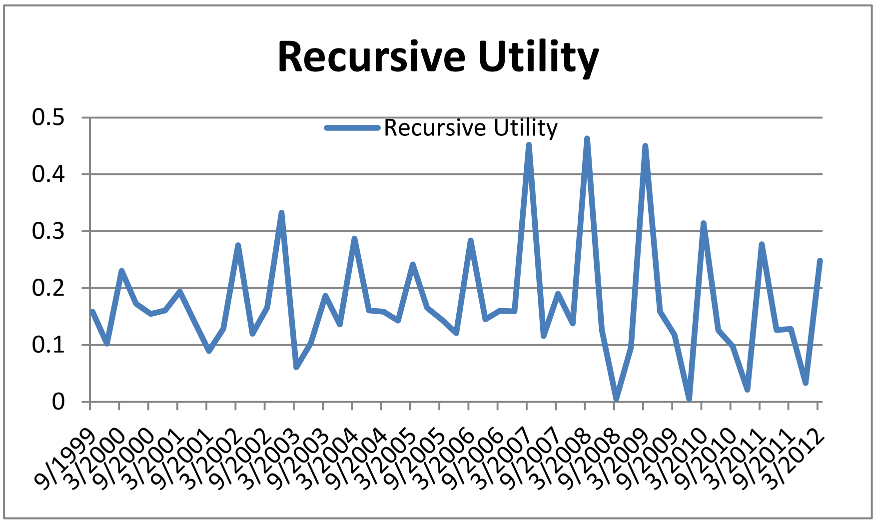


Figure 4d: HCCAPM:

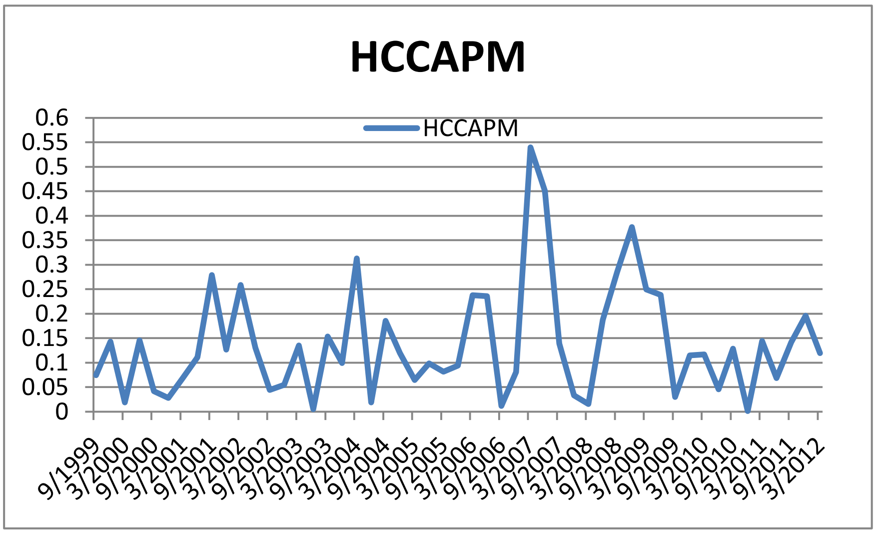


Figure 4e: H-Habit Formation model:

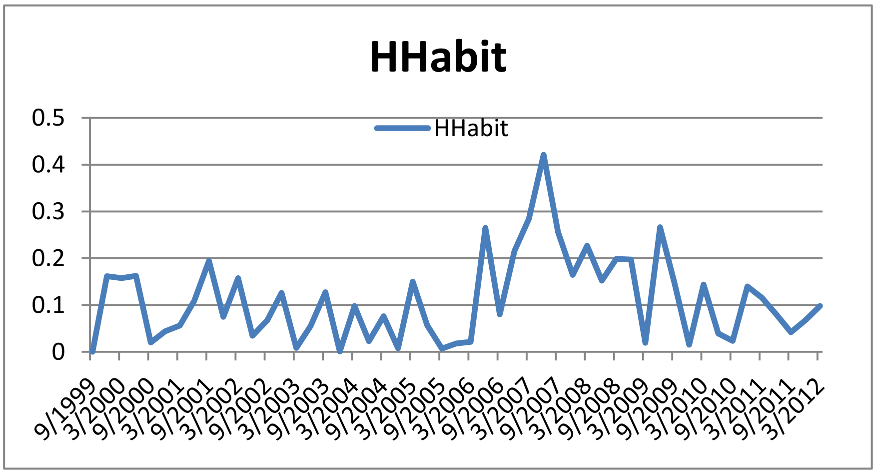


Figure 4f: H-Recursive utility model:

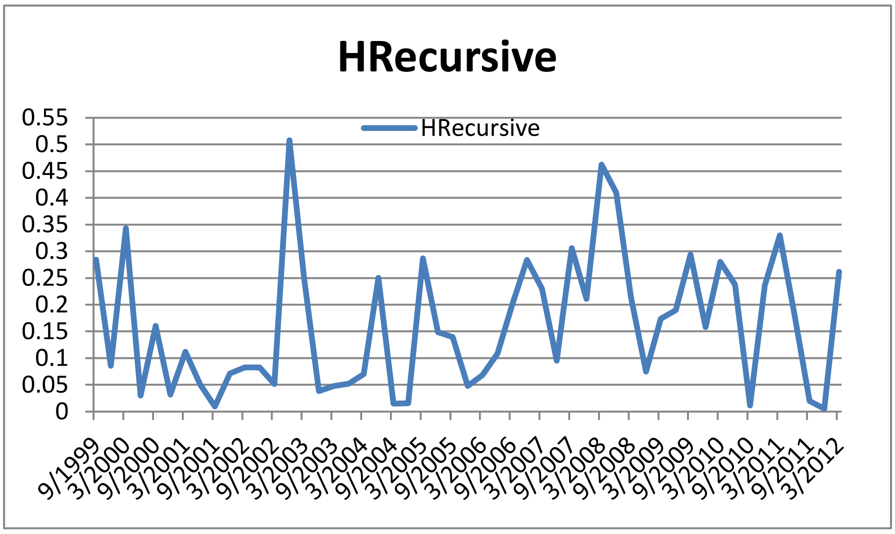


Figure 4g: Labor income model:

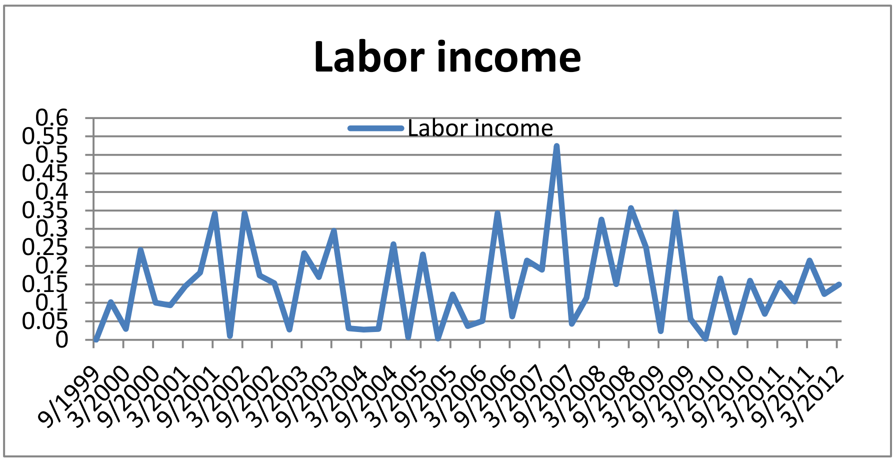
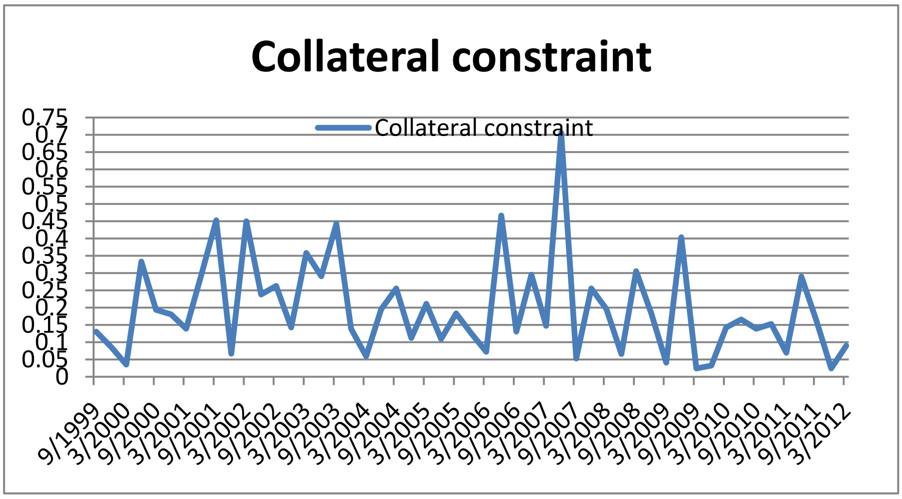


Figure 4h: Collateral constraint model:



<u>**Appendix**</u>

1. The extra data needed in housing-augmented models, labor income and collateral model:

This appendix provides more details of the data needed for housing-augmented models, labor income model and collateral constraint models. On top of the main variables mentioned in the main text, we still need some extra data sources to estimate models stated above:

(1) For housing-augmented models, especially for Housing-Habit formation model and Housing-Recursive utility models, the Euler equations require the data of total market value of the housing stock, housing stock and non-durable and service consumption "levels". These data are got from China Monthly Economic Indicators, published by National Bureau of Statistics, PRC.

(2) For Labor Income model, we also need data for the time spent at work at the market (in order to calculate the leisure time growth rate), the wage per capita, etc. All of these data are from China Population & Employment Statistics Yearbook.

(3) For Collateral Constraint Model, we need extra data for short-run and long-run risk free rate. We get the quarterly data for the yield of one-month short run risk free rate from CEIC database. And we use the 10-year risk free rate as long run risk free rate which is also from CEIC database.

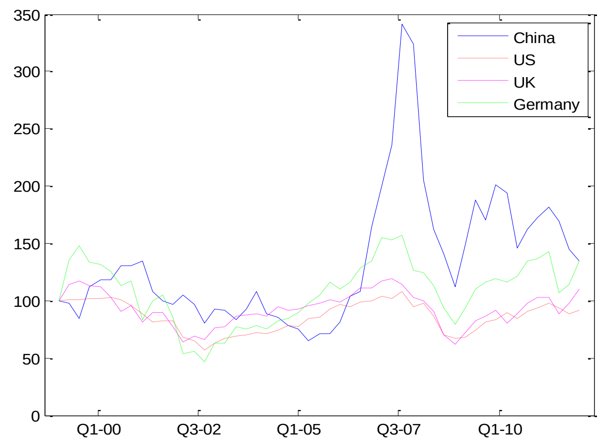
All the statistics for extra variables are summarized in the following table:

variables	mean	s.d	max	min
market value for house stock	2,586,346	2,969,512	13,994,054	84,826
consumption level	2261.5	877.3856	4320.1	1150.5
working time growth rate	1.0005	0.0083	1.0312	0.9613
the ratio: cons to wage*leisure	0.1092	0.0226	0.1509	0.0533
long run risk free rate	0.0635	0.0063	0.0783	0.0576
short run risk free rate	0.0317	0.0035	0.0041	0.0027

2. Robustness Check for stock index comparison across countries using plain index:

For stock index comparison across countries, in the main text, we use national stock share index provided by IMF. In this appendix, we use the plain stock price index for each country: we use Shanghai Stock Exchange A share Index for China, S&P 500 Index for US, DAX Index for Germany and FTSE 100 Index for UK. The phenomenon that China's stock price index has the similar pattern with the other developed countries is enhanced by this robustness check exercise.

Figure 5: Stock price index comparison across countries with plain index:



The Summary statistics of the re-normalized stock price indices based on plain index are as follows:

	China_A share	Germany_DAX	UK_FTSE 100	US_S&P 500
Mean	133.4911	107.4480	86.0440	93.3750
Standard Deviation	58.2958	27.5504	13.2714	14.6752
Correlation with U.S. stock price index	0.2815	0.8471	0.8536	1
Serial Correlation Coefficient	0.8611	0.8702	0.9011	0.8561

3. A simple example of RMSE and MAE:

The following is a simple example to illustrate the ideas of RMSE and MAE comparison:

	POE	SOE	MAE	RMSE
Model 1	-10,3,3,1,1,1,1	0	2.86	1.58
Model 2	-4,3,3,-4,-4,3,3	0	3.43	1.31

Notes: POE: Path of Error = $\left\{e_1, e_2, \ldots e_N\right\}$, SOE: Sum of Error = $\sum_{i=1}^{N} e_i$

From this example, we notice that: (1) Although Model 1 and Model 2 have the same SOE which is equal to 0, their MAE and RMSE are different; (2) For MAE, Model 1 is smaller than Model 2; but for RMSE, Model 1 is bigger than Model 2. The reason is that the calculation of RMSE penalizes large pricing error by squaring it. And Model 1 makes one “big mistake” which is (-10). Although it “corrects” itself and makes only “small mistakes” in later periods (with 4 periods making only (1) unit of forecasting error), and hence reaches the same level of SOE over the sampling period, the RMSE of Model 1 is higher than that of Model 2. On the other hand, Model 2 makes neither “big mistake” like (-10) nor “small mistakes” like (+1) and hence achieves a higher level of MAE. Thus the ranking of the models by these two criteria may lead to the different results.