ESSAYS ON FINANCIAL AND INTERNATIONAL ECONOMICS

A Dissertation

by

XIAOJING SU

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2007

Major Subject: Economics

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Approved by:

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ABSTRACT

Essays on Financial and International Economics. (August 2007)

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Chair of Advisory Committee: Dr. Dennis W. Jansen

This dissertation is comprised of three essays. Chapter II investigates the dynamic relationship between stock returns and volume. I develop a new framework in which investors maximize their expected utility by optimally placing limit orders in the market. Because these limit orders differ in prices and quantities, transactions may occur at different prices during each trading period, and the instantaneous demand may not equal the instantaneous supply. Multiple trading periods may be necessary for stocks to reach equilibrium. A Mini-Exchange platform has been developed to simulate the trading process of the model. One outcome from the simulation suggests that, during periods of price adjustment, relatively low trading volume predicts a large absolute value change in future price. Empirical estimation by Zou (2007) shows that relatively low past trading volume indicates a relatively large price movement in the future. Her finding is consistent with the prediction of the model.

In Chapter III, I measure the out-of-sample stock return predictability based on past price information. In particular, I use several nonlinear models to address the possible nonlinearity-in-mean predictability; I also adopt economic criteria, in addition to commonly used statistical criteria, to evaluate the forecasting performance. For thirteen major international stock markets, growth stocks appear to be more predictable than the general stock markets and value stocks, especially when evaluated with economic criteria. This novel finding is robust to a number of robustness checks. Overall, my results suggest that stock prices do not follow a random walk.

Chapter IV in this dissertation turns to the effect of an aging problem in China on the real exchange rate of China. China is undergoing significant demographic changes as its population is aging and will become the biggest country that ages before getting rich. In this chapter, I extend the small open economy model with demographics and life-cycle dynamics (Faruqee 2002) by including a non-tradable sector. The simulation results show that a real appreciation exists in the Chinese exchange rate in the future. Another important finding is that the GDP per capita and consumption per capita will be lower than the case without the aging problem.

To My Grandpa

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CHAPTER I

INTRODUCTION

It took a long time for the economists to realize that the trading volume of the individual stock plays an important role in affecting the movement of the stock price. Chapter II tries to find an explanation to this basic question, that why and how the trading volume of a stock will affect its price.

There is a vast literature investigating the role of trading volume in equity markets. For example, Karpoff (1987) suggests a strong positive and simultaneous relationship between price changes and trading volume. This reflects the famous Wall Street adage: "It takes volume to make prices move." Under the rational expectation framework, Blume, Easley and O'Hara (1994) build a model and clearly show the existence of the simultaneous effect (a positive relation between volume and price changes). However, to the best of my knowledge, there are two points that are not fully discussed within the existing literature. First, like many other theoretical framework, Blume, Easley and O'Hara (1994) only allow one transaction price (equilibrium price) in each period, where all transactions occur at this equilibrium price. Market clears at this price. However, in real markets, we may observe that for a given period of time, whether 5 minutes or one day, transactions occur at various prices, and at each transaction price the supply of shares may not equal the demand of shares. Second, the above settings also makes their model akin to a snapshot of the market, without much in the way of dynamics.

In Chapter II, I model the dynamic relationship between prices and trading volume. In this model, the stock exchange is driven by limit orders. The limit orders

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The journal model is Journal of Econometrics.

are the pairs of quantity of shares and prices at which traders are willing to buy or sell. Traders generate these limit orders by maximizing their utility functions. These limit orders vary in size and price because the traders are heterogeneous in their endowments and beliefs. For example, traders receive a private signal, which is the sum of fundamental value of the stock and an error term. At each period, the market has multiple transaction prices and the demand may not equal supply at each transaction price. Traders update their orders optimally based on past price information and their new private signals. Hence the market is dynamic. It is almost impossible to find a closed form solution for this kind of problem with multiple traders for multiple periods. I construct a trading platform, Mini-Exchange, using Matlab to simulate this dynamic process. This Mini-Exchange works just like the automatic electronic exchange in the real world and the traders simply submit their limit order into this Mini-Exchange and trade.

One outcome of the simulations indicates that if there is a shock to the value of the stock, it will take some time for the stock price to adjust to its new long run (equilibrium) value, and the trading volume is relatively low at the beginning or during this adjustment process. The intuitions behind this are simple. For example, suppose there is a positive shock to the fundamental value of the stock, which is unknown. In this period, traders on average will receive higher private signals than the transaction price for previous period. However, the traders could not distinguish the higher private signal between a change of fundamental value of the stock or simply a big positive error term. The best response of their new limit orders is not to adjust the price fully according to the high private signal. Second, since most traders will receive higher private signals, there will be much more buy orders than sell orders, which causes an order imbalance, and the trading volume would be low. Eventually, the price will goes up (because of the positive shock), the imbalance between buy and sell orders will diminish, and the trading volume will pick up. Hence, a low trading volume implies a big price change in the near future, and the trading volume has prediction power to the price change.

Empirical estimations are also implemented by Zou (2007). The empirical results show that trading volume of the previous day has a significant positive effect on today's absolute return, and trading volume of several days ago past has significant negative effect on today's absolute return. This result indicates that a relatively low trading volume implies a relatively large price change, either a positive or a negative change, in the near future.

Chapter III examines the market efficiency hypothesis and the predictability of the equity market. Market efficiency usually refers to independence of the future price movement to the past information and has three form: strong, semi-strong and weak form. In this chapter, I focus on the weak-form market efficiency hypothesis. In this case, the information set only contains past price information.

To examine the weak-form efficiency of the equity market, it is almost equivalent to show whether the stock prices follow a random walk process or martingale process. One method is to investigate the predictability power of common stock returns based on past price information, which naturally follows the definition of the market efficiency. The majority of earlier works fail to reject the random walk hypothesis. The other method is to develop test based on properties of random walk process. Lo and MacKinlay (1988) propose the now-commonly-used variance ratio test, which yields a mixed result especially for the low-frequency data. The potential problem of this test method is that, the rejection of random walk hypothesis does not necessarily imply the failure of market efficiency. And this variance ratio test assume linearity and only test serial uncorrelatedness rather than martingale difference. However, a nonlinear time series can have zero autocorrelation but a non-zero mean conditional on its past history. In order to comprehensively to capture whether there is any predictability of the stock price, in this chapter I use several recently developed non-linear econometric models as well as several classic models to make the out-of-sample forecast of the stock index.

The second contribution of this study is that, I investigate not only the composite stock index, but also two other import equity style indexes, the growth stock index and value stock index, across 13 international stock markets, and make the comparison of the predictability between growth and value stock index. Composite stock market index follows the random walk process dose not imply the market efficiency for growth and value stock index. Growth and value stocks are popular used concepts for practitioners. Other than the market efficiency hypothesis, this study could also has implications for practitioners, e.g., the financial managers in equity financing decisions.

In this study, I find significant out-of-sample predictability in growth style indexes for nine of thirteen countries, however, the evidence is noticeably weaker for value style indexes and composite market indexes. I conduct a number of robustness checks and find that the main finding that growth stocks are more predictable is quite robust. Finally, in overall, my results suggest that stock prices don't follow a random walk.

Chapter II and Chapter III study certain issues for the financial markets. Chapter IV turns to look at an important factor which affects the world economy a lot, the demographic changes. Unlike other economic variables that may affect the economy only in a short time horizon, some economists believe, Demographic as well as technology shape the long-run development of the economy. These factors may determine the long-run trend of the individual as well as the world economy. For example, to explain the boom of stocks/economy of USA in the 1990s, some economists put more weight on the baby-boom generation who just enter their middle-age. These people are at their peak years in their life-cycle of earning and saving, and need to find a place to invest. With the rise of the internet technology, they choose stock market.

Demography could be a decisive factor for the long-run economy. The world now is undergoing an unbalanced and dramatic demographic change: the population is aging in most advanced and developing economies and the population is also expanding in certain part of the world, e.g. India. European countries have started the aging process for almost a century but with a slow pace, while some developed economies in Asia, e.g. Japan, Korea are aging fast recently. China is also aging fast. The share of the elderly people (aged 60 and above) in total population is projected to increase in the coming 35 years from 11% to 29%, and the elderly dependency ratio, defined as the percentage of elderly people over labor force, will be even higher. China will the biggest country that becomes aged before gets rich. The evaluation of the Chinese exchange rate is an important issue and attracts the interests from many countries. In this chapter, I investigate the effects of the aging problem in China to the real exchange rate.

In this chapter, following Faruqee (2002), I use a dynamic overlapping generations model of a small open economy, incorporated with demographic and life-cycle dynamics. I extend this model to include a non-tradable sector to introduce the dynamics of real exchange rate. Calibration and simulation show that China will have a real appreciation in effective exchange rate in the future 30 years. Another finding is that both GDP per capita and consumption per capita in China will be lower than the case without aging problem.

CHAPTER II

DYNAMICS OF VOLUME AND PRICE: A NEW APPROACH

A. Introduction

Numerous studies have investigated the role of trading volume on stock returns in equity markets. The existing empirical evidence suggests that volume plays an important role in markets. For example, Karpoff (1987) provides an excellent survey on the relationship between price changes and trading volume[1]. He documents a strong positive contemporaneous relationship between absolute value of price changes and trading volume. And as a famous Wall Street adage says: "It takes volume to make prices move." One often observes a big price change associated with very high trading volume after arrivals of unexpected news.

This chapter models the dynamic relationship between prices and trading volume. All exchanges are driven by limit orders in my model. These orders vary in size and price since they come from agents who are heterogeneous in their endowments and beliefs. The market does not necessarily clear within a single trading session, so any unexecuted limit orders will remain in the limit order book. Part of information on the limit order book is publicly revealed at the end of each trading session. Traders update their optimal orders based on this public information and their private signals. The market is inherently dynamic, and past information in trading volume has a potential to have predictive power. I construct a Mini-Exchange platform to simulate this dynamic relationship. One outcome of the simulation suggests that during the price adjustment periods, relatively low trading volume implies large absolute value

[1]For more recent empirical evidence on stock prices and trading volume, please see Campbell, Grossman and Wang (1993) and Wang (1994).

Fig. 1. Nasdaq Market Inc.

change in future prices. Empirical estimates by Zou (2007) also show that past trading volume is significantly positively related to the future price movements.

Figure 1 is a real world example. It plots the prices and trading volume of the NASDAQ Stock Market Inc (NASDAQ: NDAQ) from April 2005 to April 2006. We could observe that large trading volume is often associated with a large price change. For instance, on April 22, 2005, NDAQ closed at \$13.43, almost three dollars higher than last day's closing price. On the same day, the trading volume was almost 7 million shares. This volume was very high comparing to the average volume which was less than .5 million shares. From Figure 1 we may also have certain insight of dynamics of price changes and the role of volume. From May to November 2005, NDAQ was undergoing a period where prices increased steadily and the trading volume was low. Then prices stayed at a relatively stable level after this period and the trading volume were larger. If we think the second period as a short-run equilibrium for NASDAQ (prices were relatively stable), then previous period can be taken as the adjust period. In this example, the adjust period lasted about 5 months. It can be less in other cases, eg. several days.

Many researchers have built models to investigate the possible price information contained in the trading volume. Blume, Easley and O'Hara (1994) show the existence of contemporaneous effects (a positive relation between volume and absolute values of price changes), consistent with previous findings in the literature. Their approach begins with a standard rational expectation framework, which is pioneered by Grossman and Stiglitz (1980). They assume that the fundamental value of the risky asset, say a stock, is unknown to all traders, but the distribution of the fundamental value of the stock is public information. The construction of Blume, Easley and O'Hara (1994) model can be described as following. At the beginning of a period, each trader receives a private signal, which could be the sum of the fundamental value and a noise term. The variance of the noise term is also public information. Each trader forms her expectation on the value of the stock based on her private signal and the public information, and then generates the price and quantity that she is willing to buy or sell at during this period. Under a rational expectation framework, all traders have a common belief on the equilibrium price equation of the stock, and each trader expects the other traders will have the same common belief and behave in the same way. Therefore, the stock price in each period will converge to the equilibrium price described by the price equation, and the quantity of trade is determined accordingly. Blume, Easley and O'Hara (1994) divide the traders into two groups. The traders from different groups receive signals from different distributions. Each group knows the precision of the signals for their own group. The key assumption is that one group also knows the other group's signal precision, while the other group does not share the extra information. Given the above setting, they show that the trading volume reveals the fundamental value of stock. Their simulation results show that a large deviation of price from its prior mean value is associated with large trading volume.

Blume, Easley and O'Hara (1994)'s work provides an explanation on the role of the volume, but the dynamics relationship between price and volume remains uninvestigated. Some empirical work shows that past trading volume has an effect on future returns. However, to the best of my knowledge, no one has explicitly built a theoretical model to investigate the dynamics of returns and volume.

Blume, Easley and O'Hara (1994) only allow one transaction price (equilibrium price) in each period, where all transactions occur at this equilibrium price[2], and the market clears at that price. This simplified feature makes their model akin to a snapshot of the market, without much in the way of dynamics. In real markets we may observe that, for a given period of time, whether 5 minutes or one day, transactions occur at various different prices, and at each transaction price the supply of shares may not equal the demand for shares.

My model allows for the existence of different transaction prices within a trading period, so as to more closely mimic the real market. Each trader forms her expectation on the value of the risky asset (the stock), based on her private information and public information. Then the trader generates the price and quantity she would like to trade, and she submits limit orders to the market. Under this framework, orders will be executed at different prices, the demand for shares at a given price may not equal to the supply of shares, and some orders may not be executed at all. The model is difficult to solve analytically, so I adopt a simulation method to investigate this dynamic process, and to trace the evolution of price and trading volume.

In order to carry out the simulation, a MINI-Exchange platform is developed

[2]Other discussion on equilibrium price in stock market can be found in Blume and Easley (1984).

using Matlab, which acts as a real automatic electronic stock exchange. The traders submit their limit orders into the MINI-Exchange, orders are matched based on price and time of submission. Results are returned to the trader, and all transactions and trader information are recorded for future analysis. For any given trading period, the trading volume is the sum of the quantity of all transactions within the period, and the price of the last transaction within this period is used to represent the price of this period. This process is meant to mimic what happens in the real world, with the restriction that there is only one stock traded. This simulation-based MINI-Exchange model is an innovation over the existing literature[3].

This model successfully replicates some of the phenomena in real markets, such as the finding that the trading volume is relatively low during the price adjustment process and becomes relatively high thereafter. In my simulations, there are two shocks being generated. The shock to the fundamental value of the stock is unobservable. The other shock is a shock to the mean value of the stock, which can be observed by all traders. The shocks, especially the unobserved shock, lead traders to adjust their orders according to the new private information. Because they cannot distinguish whether private signal is due to a change in fundamental value or simply a large transitory error, the shock will cause price adjustments and an imbalance between buy-side orders and sell-side orders. This leads to low trading volume before the price has fully adjusted to the shock. The length of the adjustment process depends on a variety of factors, for example, the number of traders in the market. Another finding worthy mentioning is that, because of risk aversion in the utility function of individual traders, the long-run transaction price is lower than the true value of the underlying asset.

[3]Goettler, Parlour and Rajan (2005) also provides an example on simulation.

So far in this chapter, I do not focus on simulating the contemporaneous relation between volume and prices. I postulate that by adding noise traders or allowing for asymmetric information among traders, or allowing the number of the traders to vary[4], I will find the contemporaneous effect in my simulations. This is left as a future research topic. The main findings from my simulation estimation is relatively low trading volume implies a relatively large price change, either a positive or negative change, in the near future. This simulation result has been verified by using real data. Zou (2007) apply the mixture normal distribution to IBM returns in studying the dynamics between volume and prices. Her work supports my empirical findings. We then can say trading volume plays a role in predicting the price changes.

The rest of this chapter is organized as follows: Section B describes the model, section C presents the simulation procedure and results, and the final section E concludes this chapter.

B. The Model

This section describes how an individual trader determines her limit order, namely, for a given price, how much shares she would like to buy or sell. The limit order is generated based on the information of private signal, current public information and previous transaction information. My model is built based on the standard approach of Blume, Easley and O'Hara (1994), however, I differ from them by not assuming a unique equilibrium price for a given trading period and allowing for multiple transaction prices.

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[4]One simply explanation of this contemporaneous effect is that not all traders are active in trading one stock generally, however, all traders will rush to the trading floor when news are announced, which will surely push up the trading volume.

1. Private Expectation of the Value of the Stock

Individual trader can receive a private signal about the fundamental value of the stock at the beginning of a period. In the simulations I let some traders receive a private signal only once, while the others may repeatedly receive private information. Each trader will then form an expectation on the value of the stock based on her private signal and public information. In this particular case, the public information includes the mean and the variance of the true value of stock and the variance of the error term (note that the mean for the error is zero).

First, the true value of the stock, denoted by ψ, is determined by a random draw from a normal distribution with mean ψ_0 and variance $1/\rho_0$.

$$\psi \sim N(\psi_0, 1/\rho_0)$$

where ψ_0 and ρ_0 are known to all traders while ψ isn't. Intuitively, we can think of the mean value ψ_0 as a known value of the firm or stock, which is inferred from the financial statements, or a consensus value of the stock estimated by a bunch of analysts. This value is the mean value of the firm/stock and is known to the public. While the true value of the stock ψ may be different from the above mean value and is unknown to all traders. I assume that the true value follows a normal distribution with a known variance.

Each trader receives a private signal y_{it} on the true value of the stock at the beginning of a period t. In a simplified setting, the private signal is given by:

$$y_{it} = \psi + \varepsilon_{it} \tag{2.1}$$

where the error term is distributed as

$$\varepsilon_{it} \sim N(0, 1/\rho_\varepsilon)$$

the parameter ρ_ε is known to the public. ρ_ε is also the measure of precision. The larger the ρ_ε is, the higher the precision will be, and the more accurate information the signal provides.

After receiving the private signal, each trader forms the expected value of the stock as:

$$E\{\psi|H_{it}\} = \frac{\rho_0}{\rho_0+\rho_\varepsilon}\psi_0 + \frac{\rho_\varepsilon}{\rho_0+\rho_\varepsilon}y_{it} \tag{2.2}$$

$$\text{var}\{\psi|H_{it}\} = \frac{1}{\rho_0+\rho_\varepsilon} \tag{2.3}$$

where H_{it} is the information set for individual trader i, containing private signal y_i, public information of ψ_0, ρ_0 and ρ_ε.

2. Individual Trader's Maximization Problem

For a given price, traders find the quantity of shares they want to buy or sell through a utility maximization procedure. The pair of quantity and price is thus the limit order submitted into the market. In this chapter, traders are only allowed to submit Limit Orders[5].

Traders maximize negative exponential utility functions of the form

$$U = -\exp\{-\omega_{it}\} \tag{2.4}$$

[5] Limit Orders is the most popular type of orders in the stock market. The buy (sell) limit order could only be executed at the price equal or lower (equal or higher) than the price set by the trader. For example, suppose currently, the stock is traded at \$15 per share, a trader may submit a limit order such that to buy 10 shares at the price of \$10 for each share. This limit order will not be executed until some seller is willing to sell her shares at or lower than \$10 per share.

where

$$\omega_{it} = n_{it-1} + (d_{it} + x_{it-1})\psi - p_{it}d_{it} \tag{2.5}$$

ω_{it}, the total wealth at the end of period t consists of two parts, the wealth from cash holding (or other assets, assume fully liquid) n_{it-1} at the end of period $t-1$, and the wealth from holding certain shares of stock. x_{it-1} is the number of share holdings at the end of last period $t-1$. d_{it} is the quantity of shares trader i would like to buy or sell and p_{it} is the price. Thus the pair (d_{it}, p_{it}) is the limit order submitted at current period t. If $d_{it} > 0$, it is a limit buy order, which states that the trader would like to buy this amount of shares at price p_{it} or lower. $d_{it} < 0$ stands for a limit sell order, which states that the trader would like to sell this amount of shares at price p_{it} or higher. $d_{it} = 0$ means the trader would not trade at this period. ψ is the true value of the stock. According to above settings, the cash holdings at the end of period t would be $n_{it} = n_{it-1} - p_{it}d_{it}$ and the number of share holdings at the end of period t would be $x_{it} = d_{it} + x_{it-1}$. Hence the end period wealth could also be written as

$$\omega_{it} = n_{it} + x_{it}\psi \tag{2.6}$$

Intuitively, for a limit buy order, the lower the price submitted, the lower the chance this order will be executed and vice versa. I introduce a simple form of the execution probability function in trader's maximization problem. When the trader chooses the pair (d_{it}, p_{it}) to form the limit order at the beginning of a period, she also needs to take the probability of execution into consideration. Now the maximization problem becomes

$$\max_{p_{it},d_{it}} \quad E\left\{U|_{p_{it},d_{it}}\right\}\times\text{prob(Execution)}+E\left\{U|_{p_{it},d_{it},\text{no execution}}\right\}\times(1-\text{prob(Execution)}) \tag{2.7}$$

The first part represents the results of a successful trading and the second part represents the results of failure of an execution. Orders can be unexecuted if a limit buy bids a too low price, or a limit sell asks a too high price.

It's true that the number of shares a trader would like to trade may affect the probability of execution. However, I rule out such case in my model by only allowing traders to submit limit orders with a small amount of shares. Therefore, in my model only price would affect the probability of execution. I further assume the probability of execution simply follows a CDF function of a normal distribution. The mean of the distribution is the mid-point of last period's ask and bid prices, and the variance is the bid-ask spread of last period. Then the probability function of execution is given by

$$\text{prob(Execution)} = \text{prob}(p_{it}) = \text{CDF}_{Normal}\left(\frac{p_{it} - \left\{\frac{\text{Ask}_{t-1}+\text{Bid}_{t-1}}{2}\right\}}{\sqrt{\text{Ask}_{t-1} - \text{Bid}_{t-1}}}\right) \tag{2.8}$$

Since the true value of the stock, ψ is a random variable with normal distribution, the wealth ω_{it} is a function of ψ would also be a random variable with normal distribution. Note that, for any random variable ω with normal distribution, the expectation of its exponential function is as follows.

$$E\left\{\exp(\omega)\right\} = \exp\left(E\{\omega\} + \frac{1}{2}\text{var}\{\omega\}\right) \tag{2.9}$$

Then the expectation of the individual trader's utility function is

$$E\left\{U\right\} = E\left\{-\exp(-\omega_{it})\right\} = -\exp\left(-E\{\omega_{it}\} + \frac{1}{2}\text{var}\{\omega_{it}\}\right) \tag{2.10}$$

So that the maximization problem becomes:

$$\begin{aligned}\max_{d_{it},p_{it}} \quad & -\exp\Big\{ -\left[n_{it-1} + (d_{it}+x_{it-1})E\{\psi|H_{it}\} - p_{it}d_{it}\right] \\ & +\frac{1}{2}(d_{it}+x_{it-1})^2\text{var}\left\{\psi|H_{it}\right\}\Big\} \times \text{prob}(p_{it}) \\ & -\exp\Big\{ -\left[n_{it-1} + x_{it-1}E\left\{\psi|H_{it}\right\}\right] \\ & +\frac{1}{2}x_{it-1}^2\text{var}\left\{\psi|H_{it}\right\}\Big\} \times (1-\text{prob}(p_{it}))\end{aligned} \tag{2.11}$$

Since the exponential function is a monotonically increasing function, the following maximization problem is used in the simulation.

$$\begin{aligned}\max_{d_{it},p_{it}} \quad & -\Big\{ -\left[n_{it-1} + (d_{it}+x_{it-1})E\{\psi|H_{it}\} - p_{it}d_{it}\right] \\ & +\frac{1}{2}(d_{it}+x_{it-1})^2\text{var}\left\{\psi|H_{it}\right\}\Big\} \times \text{prob}(p_{it}) \\ & -\Big\{ -\left[n_{it-1} + x_{it-1}E\left\{\psi|H_{it}\right\}\right] \\ & +\frac{1}{2}x_{it-1}^2\text{var}\left\{\psi|H_{it}\right\}\Big\} \times (1-\text{prob}(p_{it}))\end{aligned} \tag{2.12}$$

In order to investigate the dynamics of prices and trading volume, multiple periods, 100 periods, have been evaluated in my simulation, and for each period, multiple traders are studied. It is difficult to find a closed form solution for such a complicated problem, hence simulation method is used. Next section presents the simulation procedure and main results.

C. The Simulation

I construct a trading platform to match the buy and sell limit orders. Each matched buy and sell order is called one transaction, and the executed price is the transaction price. For each trading period, volume is defined as the sum of quantity of all transactions within that period, and the last transaction price is the price of that period.

Both volume and price are defined as in real life environment. When I simulate the trading process, I record trading volume and price for every trading period, and I found that relatively low past trading volume indicates a larger price movement in the future.

I demonstrate the trader's behavior and the dynamics of prices in a simulated real trading environment. 30 traders are randomly generated. They choose their optimal limit orders based on their information and trade for at least 100 periods. Detailed description and results on the baseline simulations are shown in the following.

1. Baseline of the Simulation

In each period, there are two types of traders. One kind is repeated traders, the other kind is new traders. New traders for period t are the traders first enter and trade in the market at t, and they only trade in period t. Repeated traders are defined as the traders who can trade in the market continuously after they first enter the market. Each new trader has random amount of cash and shares of stock as endowment when they first enter in the market. The repeated traders are also randomly allocated cash and initial holding of stock when they first enter the market. Therefore, the liquidity of the stock is provided by traders, which is similar to many previous research work. Unlike Blume, Easley and O'Hara (1994), I do not assume that the supply of the stock is fixed and provided exogenously. Each new trader receives a private signal at the beginning of the period when she enters the market, and she determines her limit order based on her private signal and common information. However, the repeated traders receive their private signals only once when they are the new traders and first enter the market. The holdings of repeated traders on cash and stock are the trading results from previous periods. The assumption imposed on repeated traders about private signal is not so realistic. I will relieve this assumption in the future stage of my research by including the procedure to update repeated traders' signal.

For the key parameters in the baseline simulation, the fundamental value of the stock and its mean are set equal to \$30, $\psi = \psi_0 = \$30$. The minimum scale of the limit order price and quantity that a trader can submit is 1 cent and 0.01 shares, respectively. For example, a limit order that a trader submit can be a pair of price and quantity, where price=\$28.56 and quantity=1.21 shares. The variance of the stock price $\frac{1}{\rho_0}$ is set equal to \$25, and the variance of the private signal's error, $\frac{1}{\rho_\varepsilon}$ is also \$25. Both of them have standard deviation equal to \$5. According to $E\left\{\psi|H_{it}\right\} = \frac{\rho_0}{\rho_0+\rho_\varepsilon}\psi_0 + \frac{\rho_\varepsilon}{\rho_0+\rho_\varepsilon}y_{it}$, equality of the two variances means the weight on the private signal y_{it} and the common knowledge on mean value of stock ψ_0 are the same. In such case, traders take both sources of information equally important when they form their expectation on liquidity value of stock. At the beginning of each period, every new trader receives a private signal, and she is endowed with some cash and certain shares of the stock. The private signal is based on $y_{it} = \psi + \varepsilon_{it}$. The endowment of cash is a random draw from a uniform distribution between \$150 and \$300, and the endowment of stock holdings is a random draw from a uniform distribution from 0 to 1.5 shares (the minimum scale is .01 shares).

Currently, I consider two types of baseline models. Baseline model I has new traders only and Baseline model II has both new and repeated traders. In baseline model I, every period 30 new traders are allowed to enter in the market. They receive their signals and form their expectation on value of stock, then they submit their optimal limit orders to the Mini-Exchange. Each trader can submit one and only one limit order at each period. At the end of each period, any unexecuted orders will be cancelled. Baseline model I can be thought of the stylized case in short term. For example, if each period represents 5 minutes, then a trader may not trade at every period. For a short term, we can think all traders are "new" traders at each period.

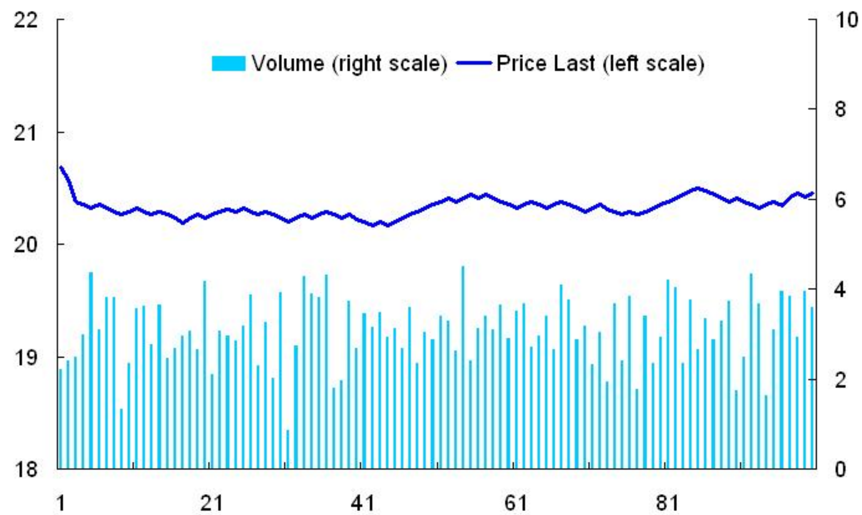

Fig. 2. Baseline I with Only New Traders

The total number of trading periods is set to be 100. Figure 2 plots every period's price and trading volume for Baseline model I.

Baseline model II considers the case including repeated traders. Repeated traders can submit limit orders at every period according to the market condition. She has initial cash and stock holdings when she first enters the market. After that, her cash and stock holdings are determined by her submissions and executions of limit orders. For repeated traders, any unexecuted order at the end of each period will remain in the limit order book. Repeated traders can cancel the unexecuted orders and resubmit new orders when they re-enter the market. In Baseline model II, I construct a repeated trader pool, which has 300 repeated traders in total. Each period I randomly select 30 out 300 repeated traders to re-enter the market. If all traders in the market are repeated traders, under current model setting, without new information or shocks, the market will soon converge to no trade. In order to study the price adjustment period, I arrange 5 new traders each period to provide the liquidity. This simulation

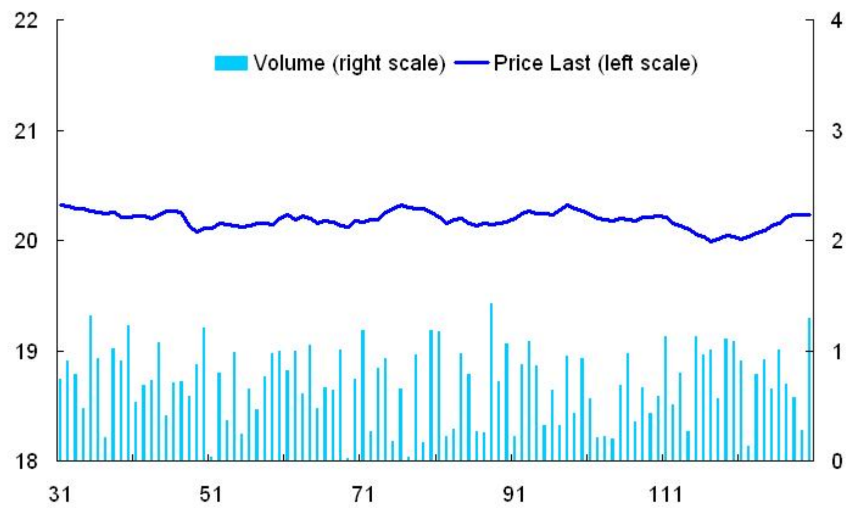

Fig. 3. Baseline II with Both New and Repeated Traders

setup can be thought as one case happened in real environment. Suppose each period stands for one day. There can be 300 traders focus on this stock and trade repeatedly. However, not all of them will trade this particular stock everyday. For example, if they trade this stock every 10 days, then on average 30 repeated traders are trading in one day. Also there are 5 new traders who are interested in this stock and trade only for that day. Figure 3 presents the result for Baseline model II.

Both Baseline model I and Baseline model II demonstrate that there exists a "long term equilibrium" trading price, which is much lower than the fundamental value of the stock ψ. The reason comes from the negative exponential utility function $U = -\exp\{\omega\}$. The absolute risk aversion of this utility function is equal to 1. Traders are reluctant to invest in a risky asset, and they will not buy the risky asset at its fundamental value. Baseline model II has a lower trading volume than Baseline model I. This is because all traders in Baseline model I are new traders, information and market are new to them. While most traders in Baseline model II are repeated traders, they adjust their portfolio less than new traders when they re-enter the market.

2. The Shock

The trading price of a stock may be quite stable over the long run unless some news or shocks occur. In this chapter, I consider two types of shocks: shock on the fundamental value, ψ, and shock on its mean value, ψ_0. At current stage, I only consider two cases. One is baseline model I (only has new traders) receiving the shock on the fundamental value. The other one is baseline model II (has both new traders and repeated traders) receiving the shock on its mean value.

a. Shock on ψ

As mentioned earlier, the fundamental value ψ is not public information. If there is a shock on ψ, no one knows the exact change on ψ. This piece of information will spread to the traders only through the new private signals. New traders enter the market after the shock will find that their private information is quite different from last period's trading price. However, they cannot distinguish whether it's due to a change on fundamental value or error of his signal. So the best response is not to adjust their limit order prices fully to the change of private signals. Thus it takes time for price to adjust to a new level which fully reflects the change in fundamental value. During the adjustment process, the buy side orders and sell side orders are in imbalance, the trading volume will be relatively low. Figure 4 shows the above phenomenon. In this simulation, true value ψ is increased by 20%, from \$30 to \$36, which occurs at period 51. All other parameters are the same, including the mean value ψ_0 which remains at \$30. During the adjustment periods, We observe that the trading volume is relatively low.

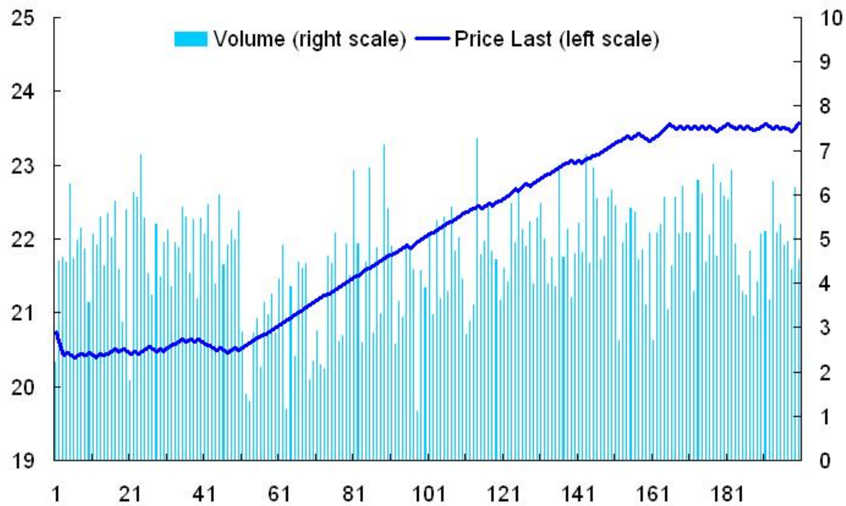

Fig. 4. Shock at ψ on Baseline I at Period 51

b. Shock on ψ_0

The mean value ψ_0 represents the public information. Intuitively, ψ_0 can be thought as inferred value of the stock from published financial statement, while the true value of the stock/firm may be different from this mean value and is unknown to the public. A shock on ψ_0 can be a new newly issued financial statement which is quite different from the previous issue[6]. This may cause a change in traders' expectation on value of the stock, but the fundamental value may remain unchanged.

When simulating the shock in Baseline model II, a 20% increase is given to the mean value ψ_0 (ψ_0 increases from \$30 to \$36), while the fundamental value ψ remains unchanged at \$30. This shock happens at period 76. The repeated traders who re-enter the market at period 76 do not receive new signal regarding to the shock. But

[6]Using new financial statement to explain the shock may not be very accurate, because the new issue is expected and the contents of which are forecasted and partially incorporated into the price before publication.

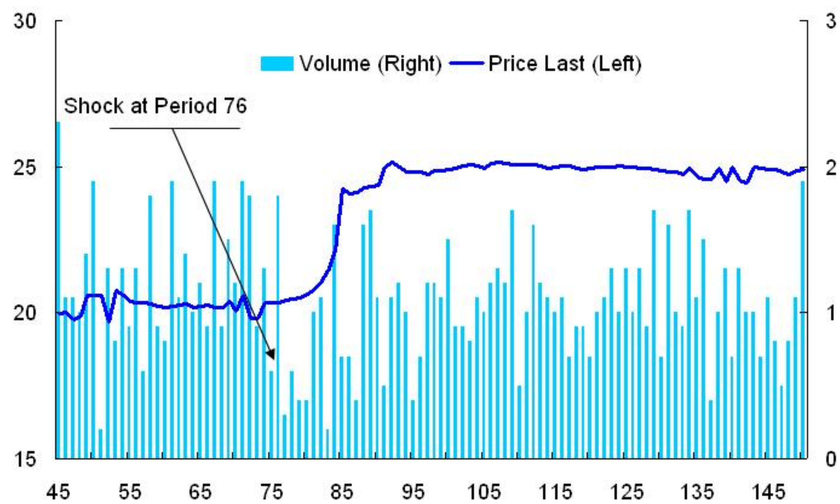

Fig. 5. Shock at ψ_0 on Baseline II at Period 76

they can notice this shock in the change in mean value, they then will change their expectation on stock value and adjust their limit orders accordingly. The new traders will immediately pick up this information and generate their optimal limit orders. It appears that it takes several periods for all of the repeated traders to pick up this information and adjust their limit orders. Figure 5 shows the result of a shock on ψ_0. We can also observe that at the beginning of the price adjustment process, the trading volume is relatively low. The adjustment time is much shorter than the case with shock on ψ. The possible reason is explained as follows. There are unexecuted orders in the limit order book submitted by repeated traders. When the shock occurs, not all of the repeated traders re-enter the market and adjust their orders at that period. So those orders in the limit order book with relative high sell prices may be matched up with the new orders with high buy prices. Thus the price increases more rapidly than the Baseline model I case.

D. Empirical Estimation

Empirical Estimations are performed by Zou (2007). In her paper, she empirically estimates the dynamics or relationship between price changes and trading volume for individual stocks.

1. Empirical Model

Trading volume reflects current market condition and imbalances between buy side orders and sell side orders, and also reflects the current view and traders' expectation of the stock. Therefore trading volume has implications for future price movements. Intuitively, a relatively low trading volume indicates that few traders are willing to trade at current price, implying price adjustments in the near future. Since the price adjustments may be positive or negative, the empirical model in Zou (2007) evaluates the dynamics between the absolute value of returns and trading volume of individual stocks. One of the models employed in Zou (2007) is described below.

$$r_t = \alpha + \sum_{i=1}^{p} \beta_i r_{t-i} + \sum_{j=1}^{q} \gamma_j V_{t-j} + \varepsilon_t \tag{2.13}$$

r_{t-i} is the absolute value of return at time $t-i$ and V_{t-j} is the trading volume at time $t-j$ where a trading volume is defined as the summation of all transaction volumes during one period.

2. Data and Estimation

In Zou (2007), Empirical data include several large stocks which are members of S&P 500 index. The prices, number of shares traded and number of shares outstanding are obtained from Datastream. The trading volume is detrended according to Llorente et al (2002). Table I and table II present the estimation results for IBM and GE.

Table I. Empirical Estimation for IBM Stock

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Const.	0.755	0.060	12.599	0.000
Abs. r(-1)	0.112	0.025	4.476	0.000
Abs. r(-2)	0.075	0.021	3.651	0.000
Abs. r(-3)	0.084	0.021	4.045	0.000
Abs. r(-4)	0.115	0.021	5.569	0.000
Abs. r(-5)	0.110	0.021	5.311	0.000
Volume(-1)	**0.403**	0.093	4.330	0.000
Volume(-2)	-0.066	0.085	-0.771	0.441
Volume(-3)	0.008	0.085	0.094	0.925
Volume(-4)	-0.095	0.085	-1.111	0.267
Volume(-5)	**-0.204**	0.079	-2.591	0.010

For the case of IBM (Table I), the coefficient for $Volume_{t-1}$ is significantly positive and coefficient for $Volume_{t-5}$ is significantly negative. These results indicate that the trading volume indeed has certain prediction power to the price changes. The positive coefficient for volume at period $t-1$ may support the simultaneous effect that the prices need volume to move. The negative coefficient for volume at period $t-5$ demonstrates that relatively low trading volume implies a significant change in the prices in the near future. Table II, the case of GE, also demonstrates the similar pattern. Coefficient for $Volume_{t-1}$ is significantly positive and coefficient for $Volume_{t-2}$ is significantly negative.

Table II. Empirical Estimation for GE Stock

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Const.	0.590	0.049	11.969	0.000
Abs. r(-1)	0.102	0.019	5.198	0.000
Abs. r(-2)	0.149	0.019	7.703	0.000
Abs. r(-3)	0.047	0.019	2.494	0.012
Abs. r(-4)	0.091	0.019	4.797	0.000
Abs. r(-5)	0.108	0.018	5.744	0.000
Abs. r(-6)	0.052	0.018	2.801	0.005
Volume(-1)	**0.140**	0.060	2.336	0.019
Volume(-2)	**-0.120**	0.060	-2.006	0.044

E. Conclusion

This chapter investigates the relation of trading volume and price movements. It is generally believed that a large price change is often associated with large trading volume. As the old Wall Street adage says: "It takes volume to make prices move." As trading volume plays such an important role in the price adjustment process, we can utilize this information to gain further understanding of price changes.

I propose a model to explain the dynamics of price and trading volume. Because it is hard to find an analytical solution for this model, I use simulation methods. A trading platform, Mini-Exchange, is developed using Matlab. There are indeed many theoretical models being developed to study microstructure of financial market, but too many not-so-realistic assumptions have been made to solve the model. This exchange platform provides a brand-new approach to solve the theoretical model.

Traders simply generate their limit orders based on this model, and submit these orders to the Mini-Exchange to trade.

Simulation results demonstrate similar pattern to those we see in real-world stock prices, as the real movement of the stock shown in Figure 1. During the price adjustment process, the trading volume is relatively low. Regression analysis by Zou (2007) on several large company stocks shows that trading volume indeed has some prediction power for price movements.

In future research, I plan to investigate many other issues based on this model. For example, by varying the number of traders, I can look ar the effect of market size. We can also look ar how the bid-ask spread can affect the trading volume and prices.

CHAPTER III

ARE GROWTH AND VALUE MORE PREDICTABLE THAN THE MARKET

A. Introduction

Whether stock returns are predictable or not has been one of the most active research topics in finance, especially since Fama's (1965) seminal work on the efficient market hypothesis. In particular, numerous authors have investigated the weak-form market efficiency, which implies that security prices follow a random walk or are unpredictable based on historical price information. Most financial economists would agree that stock return predictability is crucial for understanding the dynamics of financial markets, although there is an ongoing debate about whether it implies market inefficiency (e.g., Fama, 1965) or is consistent with rational pricing (e.g., Campbell and Cochrane, 1999; and Guo, 2004). The inference on stock predictability also has implications for practitioners. For example, portfolio managers can use it to develop trading strategies, and financial managers can use it for the equity financing decision.

However, the majority of earlier works on testing the predictability of common stock returns based on past price information fails to reject the random walk hypothesis. One possible explanation is the lack of power in empirical techniques used in these studies. To address this issue, Lo and MacKinlay (1988) propose the now-commonly-used variance ratio test but the new test at best yields a mixed conclusion, especially for the low-frequency, e.g., monthly, data. The lack of compelling empirical evidence leads Chordia, Roll, and Subrahmanyam (2005) to conclude that most financial economists and professionals still profess that asset prices are difficult to predict. This conclusion also appears to apply to the empirical test of the semi-strong form market efficiency, which I do not address in this paper. In particular, while many authors show that some financial variables help forecast the equity premium, Goyal and Welch (2006) comprehensively examine the extant empirical evidence using the data updated to 2004 but find little support for stock return predictability, especially in the out-of-sample test.

Yet, there is another alternative explanation that warrants further investigation. Both the autocorrelation test and the variance ratio test assume linearity and only test serial uncorrelatedness rather than martingale difference (Hsieh, 1991; McQueen and Thorley, 1991; and Hong and Lee, 2003). However, a nonlinear time series can have zero autocorrelation but a non-zero mean conditional on its past history (i.e., predictable based on the past history). That is, both tests may fail to capture predicable nonlinearities in mean and could yield misleading conclusions in favor of the random walk (martingale) hypothesis. In this chapter, I reexamine stock return predictability by using a comprehensive set of nonlinear models[1].

In particular, my study contributes to the literature along two important dimensions. First, while most authors focus on stock market indexes, I also comprehensively examine the martingale behavior of two most important equity style indexes, i.e., growth and value stock indexes, for thirteen major international stock markets over the period January 1975 to December 2004[2]. Testing random walk behavior of style

[1]The terms "random wal" and "martingale" have been interchangeably used in the literature. However, as discussed in Fama (1965) and Fama and Blume (1966), it is the martingale property (or unpredictability) of security prices that is of essential interest to this huge body of the literature. Strictly speaking, the innovations series is independent and identically distributed for "random walk", while it is a martingale difference sequence for "martingale".

[2]The major equity style categories are (1) value and growth and (2) small and large. However, and the style investing of small and large receives much less attention than that of value and growth possibly because many authors find that the size premium associated with the style investing of small and large has substantially attenuated since the 1980s.

equity indexes is important in itself because style investing has become quite popular in recent years and its performance benchmarks are style indexes. More importantly, equity style indexes can potentially enhance the power of my tests because recent authors suggest that they might be more predictable than general stock market indexes in both behavioral (e.g., Barberis and Shleifer, 2003) and rational pricing (e.g., Campbell and Vuolteenaho, 2004) models. Surprisingly, with the notable exception of Coggin (1998), few authors have addressed the predictability of growth and value portfolios based on their past prices (i.e., the martingale property). In this chapter, I try to fill this gap by providing a comprehensive investigation of the predictability of style indexes.

Second, I comprehensively address stock return predictability in a nonlinear, out-of-sample context. Essentially, in this chapter, I take the model selection approach (e.g., Swanson and White, 1997) instead of the traditional hypothesis testing approach as in the variance ratio test[3]. Thus, my specification addresses two major methodological deficiencies identified by Granger (1992), who suggests that *benefits can ariseespecially from considering non-linear models and that only out-of-sample evaluation is relevant and, to some extent, avoids these difficulties (due to data mining)*[4].

As conjectured, I find significant out-of-sample predictability in growth style indexes for nine of thirteen countries considered in this paper; however, the evidence

[3] As discussed in Swanson and White (1997), the model selection approach has two advantages. First, it allows us to focus directly on the issue at hand: out-of-sample forecasting performance. Second, unlike the traditional hypothesis testing approach, it does not require the specification of a correct model for its valid application.

[4] Nonlinear patterns in stock returns might arise because of (1) the GARCH-in-mean effect (Engle et al., 1987) or (2) fads or rational speculative bubbles (McQueen and Thorley, 1991). Hsieh (1991) also suggests that, if the financial market is governed by a not-too-complex chaotic process, it should have short-term nonlinear predictability but not linear predictability.

is noticeably weaker for value style indexes (five countries) and market indexes (four countries). I conduct a number of robustness checks and find that my main finding that growth stocks are more predictable than value stocks is quite robust. Although I cannot rule out the behavioral interpretation, this novel empirical evidence is particularly consistent with Campbell and Vuolteenaho (2004), who find that, compared with value stocks, growth stocks are more vulnerable to the discount-rate shock, which only has a temporary effect on stock prices. Overall, my results suggest that stock prices don't follow a random walk.

A few early authors (e.g., Patro and Wu, 2004) have addressed the predictability of international stock markets using the variance ratio test. However, these authors only focus on in-sample evidence and, more importantly, fail to allow for potential predicable nonlinearity-in-mean[5]. Also, Leitch and Tanner (1991), Hong and Lee (2003), and Campbell and Thompson (2005), among others, have emphasized the importance of using economic criteria to evaluate the forecasting performance. In the context of one-step-ahead return forecasting based on past price information, I am the first to report evidence on out-of-sample trading rule profitability (particularly based on nonlinear models) for a number of international stock markets and their stock style indexes. Consistent with early authors, I find that the (potentially nonlinear) predictability of stock prices is economically important.

The remainder of this chapter is organized as follows. I discuss econometric methodology in Section B and present empirical results in Section C. I offer some concluding remarks in Section D.

[5] Note that there is a debate about whether there exists predictable nonlinearity-in-mean in stock prices. For example, although Hsieh (1991) finds little nonlinearity-in-mean in US stock market prices, Gencay (1998) reports nonlinear out-of-sample predictability for similar indexes.

B. Econometric Methodology

To forecast stock returns, I use models for $E(Y_t|I_{t-1}$, where $I_t = \{Y_t, Y_{t-1}, \ldots\}$ is the information set available at time t. It is generally believed that Y_t is not a martingale process and has dependence in higher moment, and its conditional mean, $E(Y_t|I_{t-1}$ is time-varying in a complicated form. I will include various popular nonlinear parametric and nonparametric models used in the literature.

I use the random walk model (with a drift) as benchmark model, and consider following four popular nonlinear models to compare with the benchmark: polynomial regression model (PN), artificial neural network (NN), functional coefficient model (FC), and nonparametric regression model (NP). I also consider a basic linear model, the autoregression (i.e., AR (1)) model, which is a popular null model for modeling stock returns (Brock et al., 1992)[6].

1. The Artificial Neural Network

Artificial neural networks have been popular in capturing potential nonlinearity-in-mean in financial time series. One big advantage of neural networks over other commonly-used nonlinear time series models is that a class of multilayer neural networks can well approximate a large class of functions. There are usually two types of neural networks – namely, feedforward and recurrent networks. Similar to Gencay (1998), I use feedforward networks in this study.

The basic structure of neural networks combines many "basic" nonlinear func-

[6]I do not consider popular GARCH models in this study. As pointed out in Hsieh (1991, 1995), GARCH models capture potential nonlinearity-in-variance, but they are not designed to address nonlinearity-in-mean, which is of major interest in this study. Also see Hong and Lee (2003) for a similar point. Brock et al. (1992) and Gencay (1998) verify the failure of the GARCH and GARCH-in-mean models to help improve conditional mean forecast.

tions via a multilayer structure. Normally, there is one intermediate, or hidden, layer between the inputs and output. The intuition is that the explanatory variables simultaneously activate the units in the intermediate layer through some function Ψ and, subsequently, output is produced through some function Φ from the units in the intermediate layer. The following equations summarize this approach:

$$h_{i,t} = \Psi\left(\gamma_{i0} + \sum_{j=1}^{n} \gamma_{ij} x_{j,t}\right) \quad i = 1, \ldots, q \tag{3.1}$$

$$y_t = \Phi\left(\beta_0 + \sum_{i=1}^{q} \beta_i h_{i,t}\right) \tag{3.2}$$

or more compactly,

$$y_t = \Phi\left(\beta_0 + \sum_{i=1}^{q} \beta_i \Psi\left(\gamma_{i0} + \sum_{j=1}^{n} \gamma_{ij} x_{j,t}\right)\right) \tag{3.3}$$

where $X_{j,t}$ is the input or an independent variable (which is Y_{t-j} in this study), $h_{i,t}$ is the node in the intermediate layer (hidden layer), and Y_t is the output or dependent variable. The functions Ψ and Φ can be arbitrarily chosen and still approximate a large class of functions given sufficiently large numbers of units in the intermediate layer. Note that the correct number of lags needed is typically unknown, and in some instances lagged dependent variables may not be sufficient to capture the behavior of the time series.

As in Gencay (1998), I use single layer feedforward neural networks in this chapter. I chose the logistic function for the function Ψ and the identity function for the function Φ. Coefficients for the NN(d, q) model are estimated using nonlinear least squares via the Newton-Raphson algorithm. The final equation estimated is:

$$E(Y_t|I_{t-1}) = \beta_0 + \sum_{j=1}^{d} \beta_j Y_{t-j} + \sum_{i=1}^{q} \delta_i G\left(\gamma_{0i} + \sum_{j=1}^{d} \gamma_{ij} Y_{t-j}\right) \tag{3.4}$$

where $G(z) = (1 + e^{-z})^{-1}$ and is the function Ψ, I_{t-1} is the information set available at $t-1$, and Y_t is the dependent variable (i.e., stock returns in this study).

2. The Functional Coefficient Model

The functional coefficient model, first proposed by Cai et al. (2000), is a new nonlinear time series model with state-dependent coefficients, which includes threshold autoregression models, smooth transition autoregression, and many other regime switching models as special cases. The basic model can be expressed as follows:

$$E(Y_t|I_{t-1}) = \alpha_0(U_t) + \sum_{j=1}^{d} \alpha_j(U_t)Y_{t-j} \tag{3.5}$$

where $\{(Y_t, U_t)'\}$ is a stationary process, and Y_t and U_t are scalar variables. It is important to choose an appropriate smoothing variable U_t. U_t may be chosen as a function of explanatory variable vector Y_{t-j} or as a function of other variables. In my forecasts of exchange rates using past returns, U_t should be a certain combination of the lagged independent variables. There are several specific ways to choose U_t. Here I chose U_t as the difference between the stock return at time $t-1$ and the moving average of the most recent L periods of stock returns at time $t-1$, or:

$$U_t \equiv Y_{t-1} - L^{-1} \sum_{j=1}^{L} Y_{t-j} \tag{3.6}$$

I chose $L = 12$ to capture one-year moving average. Traders often use U_t as a buy or sell signal based on its sign, which reveals information on changes in direction. Thus, the FC model is well suited to forecasting the direction of stock price changes.

Similar to Cai et al. (2000), I estimate the term $\{a_j(U_t)\}$ nonparametrically using a local linear estimator. I approximate $a_j(U_t)$ locally (when U_t is close to u) by $a_j(U_t) = a_j + b_j(U_t - u)$. The local linear estimator at point u is $\hat{a}_j(u) = \hat{a}_j$, and

$\{(\hat{a}_j, \hat{b}_j)\}$ are chosen by minimizing the sum of locally weighted squares defined as:

$$\sum_{t=1}^{n} \left[Y_t - a_j - b_j\left(U_t - u\right)\right]^2 K_h(U_t - u) \tag{3.7}$$

where $K_h(.)$ is the kernel function used as weights for points that are included to estimate $\{(\hat{a}_j, \hat{b}_j)\}$. I use the normal distribution as the kernel function, and h is the smoothing parameter or the bandwidth of the window of the kernel function, which is determined by the modified leave-one-out least square cross-validation method proposed in Cai et al. (2000). As pointed out in Harvey (2001), the choice of the kernel function would have little effect on nonparametric regression while h is the most important factor to be considered.

3. The Nonparametric Regression Model

It is well known that nonlinearities in the conditional mean may be very complicated and cannot be expressed explicitly. Hence, it may be desirable to use the nonparametric regression to estimate the model without specifying the forms of functions. Similar to Harvey (2001), I use the well-known kernel regression technique (with some improvements on bandwidth selection to maximize the forecasting power). In general, a nonparametric regression model can be generally expressed as:

$$E(Y_t|I_{t-1}) = g(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-j}) \tag{3.8}$$

As mentioned above with respect to the nonparametric estimator of $a_j(U_t)$ in the FC model, $g(.)$ can be estimated by local linear regression. At each point $y = \{y_{t-1}, y_{t-2}, \ldots, y_{t-j}\}$, I can approximate $g(.)$ locally by a linear function $g(y) = a + (Y - y)'b$. I can also approximate $g(y)$ locally simply by a constant function $g(y) = a$(i.e., the local constant estimator), which is the approach taken here. The local constant estimator at point y is given by $g(y) = \hat{a}$, where $\hat{a}$ minimizes the sum of local weighted squares:

$$\sum_{t=1}^{n} (Y_t - a)^2 \prod_{s=1}^{j} K_{hs} (Y_{t-s} - y_{t-s}) \tag{3.9}$$

where $\prod_{s=1}^{j} K_{hs} (Y_{t-s} - y_{t-s})$ is the product kernel, $K_{hs}(.)$ is the univariate kernel function, and $h = (h_1, \ldots, h_j)$ is chosen by the leave-one-out cross-validation procedure. As already noted, the smoothing parameter h is the most important parameter in nonparametric estimation. An inappropriately chosen h will give poor in-sample and out-of-sample prediction. Traditional nonparametric forecasting uses the h that minimizes the in-sample sum square errors to forecast the next-period value based on previous in-sample data. However, while this h is optimal for all in-sample data, it may not be the best h for out-of-sample forecasting. Consequently, I use a modified method to select the smoothing parameter.

My modified approach consists of finding the best h for out-of-sample forecasting and making forecasts based on this h^*. For example, suppose that we have data points of x_1 to x_{100} and that we want to forecast x_{101}. The traditional approach is to find the best h to minimize the 100 data points' in-sample sum of squared errors (based on x_1 to x_{100}) and then use this h^* and these data points (i.e., x_1 to x_{100}) to forecast x_{101}. I propose the following modified nonparametric forecasting methodology. I use h^* and data points of x_1 to x_{80} to forecast x_{81}, data points of x_2 to x_{81} are used to forecast x_{82}, ... , data points of x_{20} to x_{99} are used to forecast x_{100}. I find the $\tilde{h}$ that minimizes the sum of squared errors of out-of-sample forecast of points x_{81} to x_{100} and use this $\tilde{h}$ and data points x_{21} to x_{100} to make my final forecast of x_{101}. In this procedure, I have two parameters to establish: (1) the out-of-sample evaluation length k is set equal to 20 ($\hat{x}_{81}$ to $\hat{x}_{100}$) in the example, and (2) the regression length m is set equal to 80 in the example. Hence, I denote the model as NP(k, m), where the parameters (k, m)

are crucial to the forecasting performance of this modified nonparametric regression model. I use several different combinations of parameters (k, m) to search for the best forecasting performance.

C. Empirical Results

1. Data Descriptions

Monthly return data for this study cover a 30-year period January 1975 to December 2004 for thirteen major international stock markets (except for Canada, for which the data start from January 1977): Australia (AU), Belgium (BE), Canada (CA), France (FR), Germany (GE), Hong Kong (HK), Italy (IT), Japan (JP), Netherlands (NE), Singapore (SI), Switzerland (SW), the United Kingdom (UK), and the United States (US). I exclude a few smaller markets considered by Patro and Wu (2004) because their growth and value stock return data are available for a very short sample period. I obtained the data of the market, growth, and value indexes for each country from Ken French at Dartmouth College[7]. Value (growth) portfolios consist of firms of which the book-to-market ratio is among the highest (lowest) 30 percentile in a given market[8]. I use returns denoted in both the local currency and the U.S. dollar and

[7]The international data are originally from Morgan Stanley Capital International (MSCI) and the U.S. data are from CRSP (the Center for Research in Security Prices) database. Patro and Wu (2004) find essentially the same results using the CRSP index and the MSCI index for the U.S.

[8]The detailed method on constructing the value and growth portfolio for each country can be found in Ken French's website, which is quoted below: "We form value and growth portfolios in each country using four valuation ratios: book-to-market (B/M); earnings-price (E/P); cash earnings to price (CE/P); and dividend yield (D/P). We form the portfolios at the end of December each year by sorting on one of the four ratios and then compute value-weighted returns for the following 12 months. The value portfolios (High) contain firms in the top 30% of a ratio and the growth portfolios (Low) contain firms in the bottom 30%. There are two sets of portfolios. In one, firms are included only if we have data on all four ratios. In the other, a firm is included in a sort variable's portfolios if we have data for that

find qualitatively the same results. For brevity, I mainly focus on the results based on returns in denoted in the local currency.

I focus on monthly return data because international value and growth return data are available to us only at the monthly frequency. It is important to note that monthly data are actually more appropriate for the purpose of this paper than daily or weekly data. This is because the higher-frequency data are more vulnerable to market microstructure problems, e.g., non-synchronous trading in stocks, which can generate "artificial" intertemporal dependencies in stock returns (Lo and MacKinlay, 1988; and Hsieh, 1991). Therefore, monthly data should provide cleaner evidence of return predictability than daily or weekly data.

2. The Results on Stock Market Indexes

I use the rolling technique to make out-of-sample forecasts. The rolling technique enables us to estimate the parameters of all the models using only a fixed-length window of past data rather than all previously available data. For example, suppose that there are n observations in total, where $n = R + P$, and P is the number of out-of-sample forecasts. In the basic rolling technique, I use the first R observations to forecast the return for period $R+1$, which we can denote P_1. Then we use observations from period 2 to period $R+1$ to forecast the return for period $R+2$, or P_2 and so on. Swanson and White (1997) suggest that the rolling technique is plausible because it further allows for the (potentially nonlinear) relation between the current and past returns to evolve across time.

One needs to use a large number of observations to estimate nonlinear models,

variable. The market return (Mkt) for the first set is the value weighted average of the returns for only firms with all four ratios. The market return for the second set includes all firms with book-to-market data, and Firms is the number of firms with B/M data.

especially nonparametric nonlinear models. Therefore, I would like to make sure that the in-sample size (R) is relatively adequate for even parsimonious nonlinear models with only one independent variable (i.e., one lagged dependent variable in this study)(particularly the three nonparametric models: NN, FC, NP). On the other hand, the out-of-sample size (P) should also be adequate to detect the difference in forecasting performance. Hence, I consider $R : P = 2 : 1$ as the ratio to have a good balance for the two considerations, which yields the in-sample size of 231 observations (with the exception of 215 observations for Canada) and the out-of-sample size of 115 observations (with the exception of 107 observations for Canada). For robustness, I also experiment with alternative ratios of $R : P = 3 : 1$ and $R : P = 4 : 1$.

I use four forecasting evaluation criteria: (1) the mean squared forecast error (MSFE); (2) the mean absolute forecast error (MAFE); (3) the mean forecast trading return (MFTR), which is defined as MFTR $\equiv P^{-1}\sum_{t=R}^{n-1} \text{sign}(\hat{Y}_{t+1})Y_{t+1}$; and (4) the mean correct forecast direction (MCFD), which is defined as MCFD $\equiv P^{-1}\sum_{t=R}^{n-1} \mathbf{1}\left(\text{sign}(\hat{Y}_{t+1})\text{sign}(Y_{t+1}) > 0\right)$. Because stock returns are volatile, forecast errors can be quite large from period to period. Therefore, the statistical accuracy of forecasts (as measured by MSFE and MSAE) does not necessarily imply economic accuracy in the sense of maximizing investor profits. For example, arguably, an investor is most interested in correctly forecasting changes in stock price movements; however, it is quite possible that wrong forecasts of price changes could have smaller MSFEs than correct forecasts of price changes. Granger (1992) emphasizes that, in this case, it is also desirable to compute economic measures of forecast accuracy, e.g., MFTR and MCFD. Many other authors, Leitch and Tanner (1991), Hong and Lee (2003), and Campbell and Thompson (2005), have made similar points in the context of forecasting asset prices. In this regard, MFTR is particularly informative to profit-maximizing investors. To summarize, the use of multiple criteria in this study provides comprehensive perspectives on the predictability of stock returns.

Tables III and IV report the out-of-sample forecast results for thirteen international stock market indexes. Note that all these results are based on the use of one-period lagged returns only (i.e., $d = 1$) because the in-sample size of just over 200 observations only allows for one independent variable (i.e., one lagged returns in this study) for several nonparametric models. I also provide bootstrapped p-values for the forecast evaluation test of whether the difference between a forecasting model and the benchmark martingale model is statistically significant.

Table III reports the results using statistical evaluation criteria MSFE and MAFE, which are in levels for the benchmark model, and in ratio relative to that of the benchmark model for the other forecasting models. The vast majority of the MSFE and MAFE ratios are greater than one, and the associated p-values for MSFE and MAFE are almost always higher than the conventional significance level. The few exceptions are the AR model for Canada and the NN model for Singapore in terms of MSFE (both significant at the 10% level) and the NN model for Singapore in terms of MAFE (significant at the 5% level). Therefore, consistent with previous studies, e.g., Hsieh, 1991, the forecasting models cannot outperform the benchmark martingale model in terms of statistical criteria. Also, the relative usefulness of the NN model compared to other nonparametric models for forecasting Singapore market is somewhat consistent with Gencay (1998). Nevertheless, although Gencay (1998) documents some evidence for significant nonlinear forecasting performance in terms of MSFE for daily Dow Jones Industrial Average indexes, I do not find such evidence for monthly CRSP value-weighted index and my finding is consistent with Hsieh (1991). This difference could be attributable to the pronounced nonsynchronous trading problem of daily price index, difference in the broad-basedness of the indexes, and difference in the sample periods, among others.

Table III. Forecast Evaluation Results for Stock Market Indexes - MSFE and MAFE

	AU	BE	CA	FR	GE	HK	IT	JP	NE	SI	SW	UK	US
							Panel A: MSFE						
Benchmark	10.71	23.16	20.83	34.11	43.88	65.01	48.47	24.83	32.13	50.93	23.99	16.34	22.33
AR	1.01	0.99	0.99	1.00	1.01	1.00	1.02	1.00	1.01	1.00	0.99	1.00	1.00
	(.88)	(.33)	(.09)	(.52)	(.73)	(.49)	(.91)	(.28)	(.66)	(.47)	(.29)	(.78)	(.77)
PN	1.02	1.01	1.02	1.00	1.17	1.01	1.06	1.04	1.08	1.05	0.99	1.04	1.02
	(.82)	(.61)	(.93)	(.55)	(.90)	(.75)	(.96)	(.88)	(.98)	(.87)	(.34)	(.94)	(.86)
NN	1.03	0.98	1.04	1.08	1.04	1.10	0.98	1.08	1.00	0.96	1.06	1.09	1.01
	(.80)	(.18)	(.93)	(.94)	(.71)	(.90)	(.29)	(.87)	(.45)	(.08)	(.75)	(.98)	(.63)
FC	1.04	1.15	1.10	1.04	1.20	1.09	1.04	1.04	1.64	1.83	2.24	1.08	1.41
	(.96)	(.95)	(.93)	(.77)	(.93)	(.72)	(.77)	(.87)	(.92)	(.90)	(.89)	(.80)	(.95)
NP	1.02	1.00	1.05	1.05	1.03	1.01	1.02	0.98	1.08	1.01	0.96	1.06	1.01
	(.86)	(.54)	(.96)	(.87)	(.80)	(.55)	(.93)	(.34)	(.89)	(.62)	(.12)	(.88)	(.82)
							Panel B: MAFE						
Benchmark	2.54	3.59	3.49	4.45	4.95	5.96	5.42	4.11	4.22	5.14	3.65	3.00	3.76
AR	1.00	0.98	1.00	1.00	1.00	1.00	1.02	1.00	1.01	1.02	1.00	1.01	1.00
	(.74)	(.15)	(.17)	(.35)	(.74)	(.70)	(.96)	(.21)	(.90)	(.97)	(.40)	(.94)	(.75)
PN	1.02	0.98	1.01	1.01	1.05	1.00	1.03	1.01	1.03	1.03	1.00	1.02	1.01
	(.94)	(.16)	(.85)	(.82)	(.88)	(.59)	(.95)	(.72)	(.97)	(.93)	(.52)	(.93)	(.69)
NN	1.01	0.99	1.03	1.05	1.02	1.07	1.02	1.01	1.01	0.96	1.01	1.05	1.00
	(.59)	(.40)	(.97)	(.94)	(.76)	(.99)	(.78)	(.60)	(.61)	(.04)	(.65)	(.97)	(.52)
FC	1.02	1.06	1.04	1.02	1.07	1.05	1.01	1.02	1.19	1.17	1.14	1.05	1.13
	(.92)	(.94)	(.85)	(.80)	(.93)	(.80)	(.62)	(.76)	(.97)	(.97)	(.85)	(.87)	(.97)
NP	1.02	1.00	1.03	1.02	1.02	1.00	1.01	0.98	1.02	1.02	0.98	1.01	1.00
	(.99)	(.46)	(.91)	(.82)	(.85)	(.56)	(.86)	(.23)	(.86)	(.73)	(.14)	(.67)	(.54)

Table IV. Forecast Evaluation Results for Stock Market Indexes - MFTR and MCFD

	AU	BE	CA	FR	GE	HK	IT	JP	NE	SI	SW	UK	US
							Panel C: MFTR						
Benchmark	0.98	1.10	1.01	1.06	0.86	0.86	1.18	0.20	0.93	0.47	0.89	0.70	0.97
AR	0.98	1.03	1.01	0.72	0.61	0.86	1.18	0.20	0.69	-0.07	0.72	0.70	0.97
		(.71)		(.88)	(.88)				(.85)	(.95)	(.76)		
PN	0.98	1.00	0.96	0.82	0.67	0.90	1.11	-0.10	0.69	0.13	0.89	0.70	0.97
		(.73)	(.89)	(.71)	(.75)	(.24)	(.60)	(.74)	(.87)	(.68)	(.42)		
NN	0.98	1.18	0.90	1.03	1.03	-0.07	1.29	0.35	1.14	1.81	1.13	0.46	0.92
		(.41)	(.77)	(.51)	(.39)	(.95)	(.16)	(.43)	(.20)	(.04)	(.29)	(.86)	(.61)
FC	0.98	1.25	1.01	0.81	1.35	0.43	1.35	-0.14	1.20	0.58	0.76	0.89	0.47
		(.35)		(.67)	(.13)	(.83)	(.32)	(.69)	(.26)	(.46)	(.66)	(.28)	(.99)
NP	0.97	1.00	0.99	0.63	0.89	1.27	0.97	0.14	0.88	1.29	1.00	0.55	0.99
	(.73)	(.74)	(.73)	(.92)	(.44)	(.13)	(.75)	(.54)	(.62)	(.07)	(.24)	(.74)	(.35)
							Panel D: MCFD						
Benchmark	0.68	0.64	0.63	0.63	0.62	0.54	0.51	0.51	0.66	0.50	0.64	0.63	0.63
AR	0.68	0.66	0.63	0.62	0.60	0.54	0.51	0.51	0.64	0.46	0.63	0.63	0.63
		(.15)		(.64)	(.86)				(.85)	(.96)	(.73)		
PN	0.68	0.63	0.62	0.62	0.61	0.54	0.50	0.53	0.64	0.52	0.63	0.63	0.63
		(.73)	(.64)	(.73)	(.57)	(.34)	(.63)	(.35)	(.86)	(.31)	(.64)	(.00)	
NN	0.68	0.64	0.62	0.59	0.60	0.51	0.52	0.57	0.66	0.63	0.66	0.56	0.63
		(.43)	(.62)	(.80)	(.69)	(.75)	(.28)	(.10)	(.32)	(.01)	(.29)	(.99)	(.45)
FC	0.68	0.67	0.63	0.62	0.63	0.53	0.53	0.54	0.63	0.50	0.61	0.63	0.57
		(.10)		(.53)	(.29)	(.58)	(.22)	(.33)	(.76)	(.44)	(.88)	(.43)	(.99)
NP	0.67	0.63	0.62	0.60	0.61	0.57	0.52	0.53	0.66	0.55	0.64	0.63	0.63
	(.72)	(.75)	(.74)	(.93)	(.59)	(.15)	(.26)	(.33)	(.33)	(.11)	(.32)	(.73)	(.35)

Table IV presents the results based on economic criteria. I find that the market index in Singapore appears to be predictable. For example, The NN and NP models outperform the benchmark model in terms of MFTR at the 5% and 10% significance levels, respectively. Moreover, The NN and NP models yield substantially higher average trading returns (1.81% and 1.29% per month for NN and NP, respectively, during the out-of-sample period) than the benchmark model (0.47%). However, I do not uncover significant predictability for the other countries.

Table IV also shows that, in terms of MCFD, in additional to very strong predictability of the direction of stock price changes for Singapore (i.e., 63% based on the NN model, which is significant at the 1% level, compared to 50% based on the benchmark), there is some (albeit marginal) evidence for predictability of the direction of stock price changes for Belgium (based on the FC model) and Japan (based on the NN model). Although the evidence is only marginally significant at the 10% level, the percentage of correct prediction of the price changes direction is indeed noticeably higher than that in the benchmark model, particularly for Japan (57% in the NN model versus 51% in the benchmark model).

To summarize, except for Belgium, Canada, Japan, and Singapore, major international stock markets appear to follow a random walk. I might attribute the predictability of Belgium, Canada, and Singapore to their relatively small market size. However, this explanation does not apply to Japan because it is the second-largest stock market.

The predictability for stock market indexes is often detected by the NN model. This result is consistent with widely perceived usefulness of artificial neural network in uncovering the nonlinearity-in-mean (e.g., Lee, White, and Granger, 1993). It is also noteworthy that none of the thirteen countries (except Italy) exhibits in-sample (linear) predictability in Patro and Wu (2004), who use the variance ratio test (see their

Table 4). Therefore, my results appear to suggest that allowing for nonlinear models and multiple evaluation criteria might increase the power for uncovering predictability of international stock market indexes, although the evidence is not extremely strong.

3. The Results on Value Style Indexes

Tables V and VI report the results for the value stock portfolios. I find significant predictability for value portfolios in three countries (Canada, Hong Kong, and the U.S.) in terms of both MSFE and MAFE (Table V). Specifically, although the evidence for Canada is significant only at the 10% level in terms of either criterion, the forecast improvements can be substantial (with the MSFE ration of 0.91 based on the NP model). The predictability evidence for Hong Kong is significant at the 5% level in terms of MSFE but only at the 10% level in terms of MAFE. Somewhat surprisingly, such predictability is captured by the simple AR(1) model but not the more elaborate nonlinear models. Nevertheless, the forecast improvements do not appear to be impressive (with the ratios of 0.99). Interestingly, the most statistically significant evidence exists for the U.S. value stock portfolio. The evidence is significant at the 5% level in terms of both criteria, and there is a noticeable forecast improvement (with the MSFE ratio of 0.94 and the MAFE ratio of 0.96, both based on the NN model).

By using economic criteria, I find the confirming evidence for predictability in Hong Kong and U.S. value stock portfolios (Table VI). Specifically, the MCFD criterion shows that the FC model can somewhat improve the percentage of correct prediction of price changes directions for the Hong Kong value stock portfolio over the benchmark model (54% versus 50%), which is significant at the 10% level. The trading return for the U.S. (1.30% per month) based on the NN model is also significantly higher than the random walk benchmark (1.14% per month) at the 10%

Table V. Forecast Evaluation Results for Value Stock Indexes - MSFE and MAFE

	AU	BE	CA	FR	GE	HK	IT	JP	NE	SI	SW	UK	US
							Panel A: MSFE						
Benchmark	11.98	31.20	37.63	55.62	59.15	130.83	74.33	52.24	65.34	101.32	61.49	28.66	17.74
AR	1.00	0.99	1.01	1.01	1.02	0.99	1.01	1.00	0.99	0.99	0.96	1.00	0.99
	(.47)	(.42)	(.73)	(.55)	(.94)	(.02)	(.68)	(.65)	(.40)	(.35)	(.15)	(.59)	(.22)
PN	1.03	1.04	0.97	1.06	1.13	1.00	1.05	1.30	1.03	1.65	1.01	1.03	1.02
	(.97)	(.77)	(.20)	(.79)	(.91)	(.51)	(.92)	(.86)	(.71)	(.79)	(.61)	(.83)	(.89)
NN	0.97	0.97	1.02	1.14	1.12	0.99	1.05	1.01	1.12	0.95	1.05	1.12	0.94
	(.15)	(.24)	(.80)	(.93)	(.91)	(.36)	(.83)	(.73)	(.93)	(.20)	(.72)	(.99)	(.03)
FC	1.07	1.07	1.17	1.65	1.16	3.04	1.13	5.45	1.24	1.99	2.20	1.67	1.04
	(.97)	(.76)	(.97)	(.89)	(.92)	(.89)	(.83)	(.92)	(.94)	(.89)	(.96)	(.97)	(.73)
NP	1.02	1.03	0.91	1.11	1.04	0.98	1.02	1.06	1.06	1.07	0.97	1.04	1.01
	(.76)	(.85)	(.06)	(.86)	(.89)	(.17)	(.88)	(.95)	(.79)	(.89)	(.18)	(.89)	(.82)
							Panel B: MAFE						
Benchmark	2.58	4.29	4.75	5.31	5.43	8.17	6.47	5.61	5.97	6.70	5.60	4.04	3.24
AR	1.00	1.00	1.01	1.02	1.01	0.99	1.01	1.00	0.99	1.01	0.99	1.00	1.00
	(.37)	(.52)	(.92)	(.88)	(.85)	(.09)	(.89)	(.31)	(.25)	(.60)	(.28)	(.51)	(.28)
PN	1.02	1.02	1.00	1.05	1.06	1.00	1.05	1.05	1.01	1.13	1.00	1.01	1.00
	(.99)	(.71)	(.37)	(.95)	(.94)	(.48)	(.96)	(.83)	(.60)	(.93)	(.57)	(.82)	(.60)
NN	0.99	1.00	1.02	1.09	1.06	1.02	1.05	0.99	1.07	1.02	1.01	1.04	0.96
	(.20)	(.44)	(.86)	(.98)	(.96)	(.80)	(.98)	(.36)	(.96)	(.72)	(.63)	(.92)	(.04)
FC	1.05	1.05	1.10	1.16	1.06	1.21	1.03	1.26	1.06	1.18	1.31	1.16	1.03
	(.99)	(.87)	(.99)	(.94)	(.88)	(.90)	(.76)	(.89)	(.90)	(.93)	(.99)	(.98)	(.83)
NP	1.01	1.01	0.96	1.06	1.03	0.99	1.03	1.02	1.02	1.05	0.98	1.02	1.00
	(.70)	(.79)	(.06)	(.92)	(.93)	(.32)	(.97)	(.89)	(.73)	(.96)	(.18)	(.87)	(.63)

Table VI. Forecast Evaluation Results for Value Stock Indexes - MFTR and MCFD

	AU	BE	CA	FR	GE	HK	IT	JP	NE	SI	SW	UK	US
Panel C: MFTR													
Benchmark	1.26	1.82	0.97	1.31	1.68	0.97	1.10	1.23	1.72	0.83	1.01	0.81	1.14
AR	1.26	1.65	0.87	1.49	1.68	0.83	1.21	1.09	1.88	0.51	1.79	0.56	1.07
		(.88)	(.89)	(.33)		(.79)	(.35)	(.74)	(.43)	(.67)	(.17)	(.74)	(.72)
PN	1.26	1.82	0.49	0.84	1.66	0.55	1.10	1.04	1.91	0.26	1.48	0.56	1.07
			(.91)	(.81)	(.52)	(.75)	(.52)	(.67)	(.38)	(.79)	(.25)	(.73)	(.75)
NN	1.25	1.64	1.10	-0.01	1.09	-0.02	0.35	1.04	1.14	2.21	0.92	0.30	1.30
	(.74)	(.71)	(.33)	(.97)	(.84)	(.78)	(.96)	(.79)	(.76)	(.06)	(.55)	(.94)	(.08)
FC	1.21	1.72	0.05	0.64	0.71	0.79	1.40	0.01	2.01	-0.94	1.49	0.40	1.03
	(.74)	(.57)	(.97)	(.80)	(.96)	(.61)	(.32)	(.94)	(.28)	(.90)	(.28)	(.91)	(.65)
NP	1.20	1.86	1.48	1.07	1.98	1.37	0.94	0.10	1.73	0.46	0.90	0.75	1.14
	(.75)	(.08)	(.25)	(.66)	(.16)	(.27)	(.65)	(.91)	(.47)	(.81)	(.66)	(.62)	
Panel D: MCFD													
Benchmark	0.72	0.63	0.62	0.64	0.65	0.50	0.51	0.57	0.67	0.51	0.61	0.60	0.63
AR	0.72	0.62	0.60	0.65	0.65	0.49	0.50	0.56	0.66	0.49	0.63	0.59	0.63
		(.85)	(.87)	(.31)		(.60)	(.65)	(.74)	(.59)	(.75)	(.25)	(.75)	(.74)
PN	0.72	0.63	0.58	0.62	0.65	0.50	0.50	0.58	0.67	0.47	0.63	0.59	0.63
			(.93)	(.79)	(.45)	(.44)	(.56)	(.12)	(.41)	(.86)	(.23)	(.75)	(.74)
NN	0.71	0.62	0.62	0.59	0.59	0.51	0.46	0.55	0.62	0.55	0.62	0.55	0.64
	(.73)	(.65)	(.44)	(.92)	(.95)	(.37)	(.86)	(.61)	(.91)	(.21)	(.37)	(.97)	(.07)
FC	0.71	0.60	0.51	0.61	0.58	0.54	0.53	0.50	0.68	0.46	0.62	0.58	0.60
	(.74)	(.85)	(.99)	(.77)	(.98)	(.06)	(.29)	(.92)	(.24)	(.84)	(.36)	(.76)	(.93)
NP	0.71	0.64	0.64	0.63	0.66	0.50	0.48	0.55	0.66	0.50	0.60	0.61	0.63
	(.61)	(.08)	(.16)	(.56)	(.22)	(.43)	(.81)	(.65)	(.62)	(.73)	(.57)	(.17)	

significance level. Based on the same NN model, there is also some evidence (significant at the 10% level) for improved prediction of price changes directions for the U.S. value stock portfolio over the benchmark model.

Table VI also shows that using economic criteria allows us to detect significant predictability of value stock portfolios in two more countries-Belgium and Singapore. The evidence for Belgium (based on the NP model) is significant at the 10% level in terms of both MFTR and MCFD. It is interesting to note that while I find that the general stock market for Singapore is predictable in terms of statistical criteria, there is no such evidence for its value stock portfolios. Nevertheless, the predictability evidence for the country shows up in terms of MFTR, which demonstrates the advantage of using both economic and statistical criteria. While the evidence is only significant at the 10% level, the associated return (2.21% per month based on the NN model) clearly dominates that (0.83% per month) of the benchmark model.

To summarize, based on the four evaluation criteria, there is evidence against random walk for value stock portfolios in five of thirteen international stock markets, namely, Belgium, Canada, Hong Kong, Singapore and the U.S. It is interesting to note that these five countries include three of the four countries of which the general stock markets are found to be unpredictable[9]. Therefore, in general, there is no clear evidence that value stock portfolios are more predictable than the market portfolio.

4. The Results on Growth Style Indexes

Table VII shows that, for growth stock portfolios, there is no evidence that any forecasting model can outperform the benchmark model in terms of either MSFE or

[9]The only exception is Japan, for which there is also some predictability evidence in terms of MCFD significant at the 15% level (with the p-value of 0.12 based on the PN model).

Table VII. Forecast Evaluation Results for Growth Stock Indexes - MSFE and MAFE

	AU	BE	CA	FR	GE	HK	IT	JP	NE	SI	SW	UK	US
							Panel A: MSFE						
Benchmark	12.73	26.71	42.38	36.05	54.53	41.37	50.83	27.87	24.61	52.29	18.83	15.44	25.18
AR	1.01	0.98	1.01	0.99	1.01	1.00	1.02	1.00	1.01	1.01	0.98	1.00	1.01
	(.93)	(.11)	(.81)	(.30)	(.74)	(.57)	(.96)	(.73)	(.93)	(.83)	(.17)	(.75)	(.79)
PN	1.02	0.99	1.04	0.98	1.08	1.01	1.02	1.02	1.01	1.02	0.99	1.06	1.02
	(.93)	(.24)	(.85)	(.20)	(.93)	(.76)	(.89)	(.81)	(.71)	(.84)	(.31)	(.99)	(.82)
NN	1.17	0.98	1.09	0.99	1.03	0.97	1.12	1.05	0.95	0.98	1.06	1.12	1.01
	(.98)	(.33)	(.92)	(.43)	(.70)	(.29)	(.99)	(.89)	(.11)	(.37)	(.84)	(.99)	(.62)
FC	1.07	1.08	2.19	1.25	1.18	1.01	1.03	1.76	1.15	1.29	1.81	2.21	2.37
	(.99)	(.83)	(.97)	(.76)	(.97)	(.54)	(.71)	(.91)	(.97)	(.97)	(.87)	(.94)	(.91)
NP	1.03	1.05	1.09	1.00	1.05	1.08	1.04	1.00	1.00	1.03	1.00	1.02	1.05
	(.78)	(.83)	(.93)	(.49)	(.83)	(.92)	(.88)	(.61)	(.70)	(.82)	(.56)	(.88)	(.88)
							Panel B: MAFE						
Benchmark	2.77	3.93	4.99	4.56	5.26	4.66	5.61	4.34	3.68	5.20	3.27	2.90	4.01
AR	1.01	0.98	0.99	0.99	1.00	1.00	1.02	1.00	1.01	1.01	0.99	1.01	1.01
	(.91)	(.04)	(.20)	(.16)	(.50)	(.82)	(.98)	(.81)	(.98)	(.94)	(.17)	(.93)	(.92)
PN	1.02	0.98	1.01	0.99	1.03	1.00	1.01	1.01	1.02	1.01	1.00	1.04	1.02
	(.98)	(.03)	(.81)	(.29)	(.89)	(.50)	(.86)	(.79)	(.87)	(.83)	(.36)	(1.00)	(.95)
NN	1.10	0.99	1.02	1.01	1.02	1.00	1.06	1.02	0.98	1.03	1.01	1.06	1.01
	(.99)	(.38)	(.75)	(.65)	(.75)	(.53)	(.99)	(.80)	(.27)	(.89)	(.67)	(.99)	(.71)
FC	1.05	1.05	1.29	1.02	1.08	1.02	1.03	1.13	1.10	1.12	1.10	1.24	1.19
	(.99)	(.85)	(.99)	(.68)	(.95)	(.62)	(.88)	(.91)	(.99)	(.98)	(.87)	(.96)	(.91)
NP	1.04	1.01	1.03	1.00	1.02	1.04	1.00	0.99	1.02	1.03	1.01	1.01	1.02
	(.91)	(.78)	(.88)	(.47)	(.76)	(.94)	(.51)	(.27)	(.95)	(.89)	(.66)	(.87)	(.83)

Table VIII. Forecast Evaluation Results for Growth Stock Indexes - MFTR and MCFD

	AU	BE	CA	FR	GE	HK	IT	JP	NE	SI	SW	UK	US
							Panel C: MFTR						
Benchmark	0.72	0.94	0.69	0.96	0.76	0.92	1.06	-0.26	0.56	0.28	0.90	0.64	0.95
AR	0.72	1.01	0.70	0.76	0.07	0.92	1.06	-0.23	0.56	0.28	0.85	0.64	0.95
		(.11)	(.08)	(.75)	(.90)			(.41)			(.59)		
PN	0.70	1.00	0.80	0.83	0.15	0.81	1.06	-0.13	0.53	-0.21	1.02	0.64	0.95
	(.74)	(.12)	(.23)	(.75)	(.87)	(.76)		(.43)	(.74)	(.87)	(.09)		
NN	0.47	0.99	0.50	0.78	1.25	1.27	0.32	0.22	0.92	1.11	0.87	0.54	0.91
	(.79)	(.47)	(.61)	(.78)	(.22)	(.22)	(.90)	(.25)	(.08)	(.10)	(.57)	(.93)	(.53)
FC	0.72	0.96	1.16	1.07	0.14	0.92	1.04	0.65	0.70	0.38	0.60	0.41	0.54
		(.47)	(.25)	(.44)	(.91)		(.50)	(.10)	(.30)	(.44)	(.81)	(.84)	(.89)
NP	0.56	0.72	0.40	1.31	1.18	0.64	0.83	0.68	0.53	0.26	0.81	0.64	0.81
	(.84)	(.86)	(.82)	(.15)	(.25)	(.84)	(.72)	(.06)	(.74)	(.52)	(.66)	(.08)	(.74)
							Panel D: MCFD						
Benchmark	0.57	0.63	0.57	0.63	0.60	0.59	0.52	0.51	0.62	0.54	0.63	0.60	0.61
AR	0.57	0.64	0.58	0.62	0.59	0.59	0.52	0.50	0.62	0.54	0.62	0.60	0.61
		(.11)	(.09)	(.73)	(.65)			(.57)			(.61)		
PN	0.56	0.63	0.57	0.62	0.59	0.59	0.52	0.47	0.61	0.51	0.63	0.60	0.61
	(.73)	(.19)	(.33)	(.65)	(.56)	(.34)		(.74)	(.74)	(.81)	(.09)		
NN	0.57	0.62	0.56	0.60	0.62	0.62	0.50	0.52	0.63	0.53	0.63	0.57	0.59
	(.48)	(.57)	(.59)	(.82)	(.31)	(.09)	(.68)	(.40)	(.20)	(.52)	(.42)	(.92)	(.70)
FC	0.57	0.62	0.61	0.68	0.57	0.59	0.50	0.57	0.60	0.54	0.61	0.59	0.56
		(.58)	(.22)	(.12)	(.73)		(.84)	(.21)	(.69)	(.47)	(.69)	(.58)	(.95)
NP	0.53	0.61	0.55	0.67	0.60	0.57	0.53	0.56	0.61	0.52	0.62	0.61	0.61
	(.86)	(.72)	(.74)	(.05)	(.39)	(.81)	(.33)	(.19)	(.74)	(.68)	(.63)	(.08)	(.42)

MAFE, with the exception of Belgium, for which both the AR and PN models outperform the benchmark model in terms of MAFE at the 5% level. However, Table VIII shows that I obtain quite different results if using economic criteria. In particular, I find evidence for predictability in growth stock portfolios in nine countries, including Belgium. This result clearly demonstrates the importance of considering economic criteria in the forecast evaluation, as Hong and Lee (2003) have emphasized in their exchange rate forecasting exercises. This result also confirms the argument of Clements and Smith (2001) that the forecast evaluation based on traditional statistical measures may fail to detect the superiority of the nonlinear models.

Specifically, there is predictability evidence in terms of MFTR in Table VIII — all of which are significant at the 10% level — for Canada, Japan, Netherlands, Singapore, Switzerland, and the U.K. In particular, trading returns based on appropriate nonlinear models are far better than those of the benchmark model for Japan (0.68% versus -0.26%), Netherlands (0.92% versus 0.56), and Singapore (1.11% versus 0.28%). For MCFD, I have the confirming evidence that the percentage of correct prediction of price changes direction can be improved over the benchmark model for Canada, Hong Kong, Switzerland, and the U.K., which is significant at the 10% level. In addition, I find new predictability evidence for France at the 5% level.

To summarize, the forecasting models considered in this paper outperform the benchmark model for nine out of the thirteen markets, including Belgium, Canada, France, Hong Kong, Japan, Netherlands, Singapore, Switzerland, and the U.K. These nine countries include all the four countries of which the general stock markets show some predictability and four of the five countries of which the value stock portfolios show some predictability. Therefore, my results suggest that growth stock portfolios appear to be more predictable than both value stock portfolios and the general stock markets.

It is somewhat puzzling that growth stocks are not predictable in U.S. but in majority of the other developed countries. One possible explanation is that the forecasting models considered here have potential limitations, for example, they do not fully exploit the information available at the time of forecast. In particular, Guo and Savickas (2004) use theoretically motivated financial variables, i.e., stock market volatility and average idiosyncratic volatility, to forecast stock returns and find that the in-sample R-Squared is substantially higher for growth stocks than value stocks. Therefore, my international evidence confirms the Guo and Savickas' finding that growth stocks are more predictable than value stocks. It is also interesting to note that, unlike the case for stock market indexes, the predictability for style stock indexes is no longer dominantly picked up by the NN model. Again, this result demonstrates the importance of considering several models rather than a single model (e.g., the neural network).

5. Robustness Check

I conduct the robustness check on the results based on alternative ratios of $R : P = 3 : 1$ and $R : P = 4 : 1$. For brevity, I only briefly summarize the main findings but detailed results are available on request. The ratio of $R : P = 3 : 1$ yields the in-sample size of 260 observations and the out-of-sample size of 86 observations. The results based on this ratio are qualitatively the same as those reported above.

I further conduct the analysis based on the ratio of $R : P = 4 : 1$, which yields the in-sample size of 277 observations and the out-of-sample size of 69 observations. Note that compared to the case of $R : P = 2 : 1$(115 observations or about 9.5 years), there is a substantial reduction in the out-of-sample size(69 observations or about 5.5 years). For a much shorter out-of-sample window, I find significant predictability in many countries. For example, in terms of at least one of the four evaluation criteria, stock market indexes are found to be predictable at the 5% significant level for two countries (Hong Kong and Japan) and at the 10% level for six countries (Australia, Belgium, Canada, Singapore, Switzerland, and the U.K.). Clearly, this evidence for stock market index predictability is much stronger than the results reported above and in previous studies (e.g., Patro and Wu, 2004). Similarly, growth stock indexes are found to be predictable at the 5% level for four countries (Australia, Canada, France, and Hong Kong) and at the 10% level for six countries (Belgium, Germany, Japan, Netherlands, Singapore, and the U.K.). In contrast, value stock indexes are found to be predictable at the 5% level for one country (Switzerland) and at the 10% level for two countries (Hong Kong and the U.S.). To summarize, although I find some interesting variations in the results based on the ratio of $R : P = 4 : 1$, the main finding that growth stocks are predictable for most international stock markets remains qualitatively unchanged.

Patro and Wu (2004) also conduct supplementary analysis based on the return data denoted in the U.S. dollar. Obviously, using stock returns in the U.S. dollar compounds the effect of exchange rate changes. While Patro and Wu find somewhat stronger predictability for market indexes denoted in the U.S. dollar, their main finding on random walk behavior of monthly stock market indexes is unaffected. I reach a similar conclusion in my analysis; for brevity, these results are not reported here but are available on request[10].

To address potential data snooping biases, I conduct White's (2000) test for out-of-sample multiple model comparisons. For brevity, I briefly summarize the main finding here but details are available on request. The majority of significant test

[10] I also consider two-step and three-step ahead forecast using the US data. As might be expected, the forecast results for two- and three-step-ahead forecast performance is generally much weaker than the one-step-ahead forecast reported above.

statistics based on a single model remains qualitatively the same. This statement is particularly true, given the concerns of potentially low power of the test (e.g., Hong and Lee, 2003) and relatively small sample sizes of this study (which together would justify the use of somewhat higher significance levels, such as 15%). At any rate, the main finding of more predictability in growth stocks than in value stocks and the market is qualitatively unchanged.

Lastly, to address the concern whether the U.S. results are robust in different sample periods (e.g., Patro and Wu, 2004), I conduct further analysis using monthly U.S. data over the period July 1926 to December 2004[11]. In particular, I investigate two subsamples: July 1926 to June 1963 (with a total of 430 observations) and July 1963 to December 2004 (with a total of 484 observations). Table IX shows that, based on the ratio $R : P = 2 : 1$, the stock market index and growth stock index are unpredictable by any model during the first period. By contrast, the NN model detects predictability in the value stock index for each of the four criteria either at the 10% or 5% levels. However, Table X shows that this finding is somewhat sensitive to the alternative ratio of $R : P = 4 : 1$, for which I find all three price indices to be predictable at the 10% level.

For the second subsample, the results (for brevity, not reported here) are qualitatively the same as those based on the data for the period January 1975 to December 2004. That is, regardless of the ratio of $R : P = 2 : 1$ or $R : P = 4 : 1$, the value stock index is predictable at the 10% level, especially when evaluated with economic criteria. However, I find negligible predictability for the stock market index and growth stock index. To summarize, the additional results for the second subsample suggest that my main finding based on a relatively short sample period January 1975

[11]Campbell and Vuolteenaho (2004) also find that CAPM explains the value premium in the pre-1963 sample but not the post-1963 sample.

Table IX. Forecast Evaluation Results for the US: 1926 to 1963 and R:P = 2:1

(R,P) = (287,143)		MSFE		MAFE		MFTR		MCFD	
k	Model	MSFE	P	MAFE	P	MFTR	P	MCFD	P
				Panel A. The Market Index					
0	Benchmark	12.43		2.82		1.15		0.67	
1	AR	1.02	0.93	1.00	0.67	1.10	0.86	0.66	0.86
2	PN	1.03	0.99	1.01	0.92	1.14	0.75	0.66	0.74
3	NN	0.99	0.31	1.00	0.50	1.14	0.71	0.66	0.76
4	FC	1.03	0.75	1.01	0.75	1.05	0.87	0.66	0.86
5	NP	1.05	0.87	1.02	0.91	1.17	0.33	0.67	0.33
				Panel B. The Value Stock Index					
0	Benchmark	17.77		3.23		1.36		0.65	
1	AR	1.04	0.92	1.02	0.91	1.39	0.09	0.67	0.07
2	PN	1.05	0.98	1.03	0.99	1.39	0.08	0.67	0.08
3	NN	1.06	0.89	1.03	0.89	1.33	0.57	0.65	0.80
4	FC	1.06	0.83	1.04	0.91	1.18	0.83	0.65	0.77
5	NP	1.05	0.91	1.04	0.99	1.28	0.74	0.64	0.92
				Panel C. The Growth Stock Index					
0	Benchmark	14.19		3.03		1.11		0.65	
1	AR	1.01	0.91	1.00	0.72	1.11	0.99	0.65	0.96
2	PN	1.02	0.93	1.01	0.96	0.94	0.90	0.64	0.79
3	NN	1.04	0.87	1.01	0.75	0.90	0.86	0.63	0.71
4	FC	1.10	0.89	1.03	0.89	0.89	0.83	0.62	0.93
5	NP	1.01	0.58	1.01	0.73	1.20	0.28	0.66	0.16

Table X. Forecast Evaluation Results for the US: 1926 to 1963 and R:P = 4:1

(R,P) = (344,86)		MSFE		MAFE		MFTR		MCFD	
k	Model	MSFE	P	MAFE	P	MFTR	P	MCFD	P
				Panel A. The Market Index					
0	Benchmark	13.76		2.97		0.80		0.66	
1	AR	0.99	0.43	1.00	0.55	0.90	0.08	0.67	0.08
2	PN	0.98	0.22	1.01	0.78	0.78	0.76	0.65	0.73
3	NN	1.02	0.69	1.02	0.81	0.68	0.72	0.65	0.75
4	FC	1.04	0.87	1.02	0.82	0.67	0.81	0.64	0.82
5	NP	1.05	0.75	1.01	0.74	0.84	0.32	0.66	0.31
				Panel B. The Value Stock Index					
0	Benchmark	18.00		3.23		1.00		0.64	
1	AR	0.97	0.20	0.95	0.03	1.01	0.48	0.64	0.25
2	PN	0.98	0.24	0.99	0.29	1.01	0.08	0.65	0.08
3	NN	0.99	0.48	0.99	0.37	1.19	0.23	0.66	0.16
4	FC	0.97	0.34	0.98	0.25	0.65	0.83	0.61	0.76
5	NP	0.99	0.43	0.99	0.42	0.93	0.74	0.63	0.73
				Panel C. The Growth Stock Index					
0	Benchmark	15.86		3.20		0.72		0.62	
1	AR	1.00	0.46	1.00	0.46	0.81	0.08	0.63	0.09
2	PN	0.99	0.37	1.01	0.77	0.71	0.53	0.61	0.68
3	NN	1.05	0.83	1.01	0.65	0.73	0.48	0.58	0.75
4	FC	1.16	0.90	1.06	0.92	0.41	0.80	0.59	0.73
5	NP	1.10	0.83	1.02	0.72	0.86	0.29	0.63	0.18

to December 2004 appears to be reliable.

D. Conclusion

This study investigates the martingale behavior of growth and value style indexes as well as general stock market indexes for thirteen major international stock markets. In addition to the linear model, I also employ several popular nonlinear models to capture potential nonlinearity-in-mean in stock returns. I find that growth stock portfolios appear to be more predictable than value stock portfolios as well as the general stock market indexes. By contrast, there is no clear evidence that value stock portfolios are more predictable than the general stock markets. To the best of my knowledge, this result is novel.

my results shed light on the recent debate about stock return predictability. Goyal and Welch (2006) reexamine the existent empirical evidence using the data updated to 2004 and find little support for the out-of-sample predictability. However, Cochrane (2006) argues that, because the dividend yield is quite volatile and the dividend growth is unpredictable, the dividend yield must forecast stock returns, especially at long horizons. In this paper, I address this issue using different assets (growth style indexes), different forecasting variables (past returns), different forecasting models (nonlinear models), and alternative forecasting evaluation criteria (economic criteria). My analysis suggests that stock returns might be predictable.

Consistent with early authors, e.g., Leitch and Tanner (1991), Hong and Lee (2003), and Campbell and Thompson (2005), I emphasize the importance of using economic criteria, in addition to commonly used statistical criteria in the forecast evaluation. Such consideration appears to be crucial to the main finding of this study. In particular, while statistical criteria fail to reject the martingale hypothesis for all the growth stock price series except one country, economic criteria suggest predictability of the direction of price changes as well as trading returns for nine countries. The evidence confirms the results reported by Hong and Lee (2003), who investigate foreign exchange rate predictability using largely similar forecasting models.

My finding that growth stocks are more predictable than value stocks and the aggregate market might be consistent with behavioral models. For example, Barberis and Shleifer's (2003) style-level positive feedback model implies that predictability of style indexes can be as pronounced or even more pronounced than the market and Teo and Woo (2004) provides further supportive evidence for their model. Also, Lakonishok et al. (1994) suggest that growth and value stocks are predictable because of the correction for the mispricing: Initially, growth stocks tend to be overpriced and the value stocks tend to be underpriced. However, my results might also be consistent with rational pricing. In particular, growth stocks are more predictable than value stocks possibly because, as shown by Campbell and Vuolteenaho (2004), the former is more sensitive to the discount rate shock, which has only a temporary effect on stock prices. In this paper, I do not try to differentiate the two alternative explanations because my main focus is stock return predictability. Nevertheless, it will be interesting to address this issue in future research.

CHAPTER IV

HOW WOULD AGING POPULATION AFFECT THE REAL EXCHANGE RATE? THE CASE OF CHINA

A. Introduction

The world is undergoing a major demographic transition[1]. The population growth is slowing its pace, and at the same time the age structure of population is also changing. As the total fertility rate constantly decreases over time, the share of the young is falling and that of the elderly is rising. However the pace of the demographic transition is much different across countries. The aging process starts at the beginning of 20th century and moves slowly over the years for most advanced countries. In a number of developing countries in east and southeast Asia and central and eastern Europe, the aging process did not start long ago, but is moving fast. These countries will experience significant aging problem at about 2020. However, in other developing countries, the aging process is not observed and working-age populations will increase in a few decades.

China, similar to other developing countries in east and southeast Asia, starts to age recently, and will become one of the fastest aging countries in the world. China started the aging process in about 1980, the time that China began its one child policy. However, the elderly dependency ratio is about 11% currently and doesn't change much during the past 20 years. Elderly dependency ratio is a measure of aging, is usually defined as the population above 65 (elderly) over the population between 15 and 65 (working age population). This number will increase to over 35%

[1]For more information on global impact of demographic change, please see Batini, Callen and McKibbin (2006).

in the next 30 years. China, thereafter, will become the biggest country that aged before get rich.

China is also in the midst of the great economic transition. China is steadily moving toward a more liberalized market and becomes more and more open to the international trades. Thus the first step towards our interests[2], we would like to look at how the aging China would affect her linkage with the rest of the world. One of the indicators I am going to investigate in this chapter, is to find how would the aging population in China affects her exchange rate.

This chapter closely follows the work of Tamirisa and Faruqee (2006). I investigate the effects of aging problem in a dynamic overlapping generations model of a small open economy[3]. Following Faruqee (2002), this model is incorporated with demographics and life-cycle dynamics. I further include a non-tradable goods sector to introduce the real exchange rate dynamics.

The effects of the aging problem of China on her exchange rates are obtained by simulations. The current and projected demographics are treated as exogenous variables and are used as the input to the model. The future values of the macroeconomic variables including the real exchange rate, are simulated based on the initial conditions of the economy and the projected exogenous path of demographic variables, such as the birth rates and death rates. The results are presented as the deviations to the baseline scenario, in which there is no aging at all.

Simulations show that population aging will have significant effects on the econ-

[2]The exchange rate of China is a hot topic recently, especially current U.S. government advocates an appreciation. There are many researches on finding the "right" exchange rate of China. For example, Dunaway and Li (2005) and Wang (2004). Isard, Faruqee, Kincaid and Fetherston (2001) and Isard and others (1998) describe the general methodology in finding the exchange rate.

[3]This model shares many features with the IMF MULTIMODE model. A general description can be found in Laxton and others (1998).

omy and in particular, the real exchange rate of China. A decline in the working-age population and an increase in the elderly population will reduce the GDP per capita. This leads to a reduction of consumption per capita. Since the production of non-tradable goods sector is constrained by the reduction of the working-age population, but the demand on the non-traded goods is not reduced much because of the increases on the elderly population, the relative price of non-traded goods to the price of traded goods will increase. This leads to a real appreciation of the exchange rate. Based on different opinion on the future demographic movements, the worst scenario indicates a 7% increase of the real exchange rate in year 2070.

The rest of this chapter is organized as follows: Section B presents the model. Section C discusses the projected data on demographics. Section D presents the simulation results and Section E concludes.

B. The Model

The model is a dynamic general equilibrium system for a small open economy. The overlapping generation framework is based on Blanchard (1985), Weil (1989) and Yaari (1965). Faruqee (2002) incorporate the life-cycle profiles of individuals' earning and demographics into the model. The two features jointly give the role of the demographics such that the changing of the demographic structure could affect many key macroeconomic variables of a economy. The evolution of the demographics is introduced by including the exogenous cohort-specific birth/death rates. These give the time-varying population growth rate and demographic structure. Life-cycle or age-earnings profile links the demographics to the real economy variables. Age-earning profiles typically have a hump-shaped pattern: earnings rise as young individuals enter the labor force, reach peak at middle age and decline thereafter. Since the behavior of an individual will be different during his life time, different demographic structure of the economy will lead to different aggregate saving-consumption behavior. This is the underlying reason that how the demographics affect the economy. I finally incorporated a non-tradable sector into above stylized model. Since one simple intuition of real exchange rate is the relative price of non-tradable goods to the price of tradable goods, I thus introduce the real exchange rate dynamics into the model. The following description closely follows Faruqee (2002).

1. Population

In finite lived overlapping agents framework, if individuals retire at a certain stage and receive zero labor income thereafter, it would cause a discontinuity problem[4], which will make it hard to apply the techniques used to solve the infinite-lived agents models. Blanchard (1985) by-passes the problem by assuming that each individual, through its whole life, faces a constant probability of death, p. The expected life of an individual is thus $1/p$, and individuals will live forever if $p \to 0$. Given a constant number of p, both total population and the structure of population will remain unchanged over time.

Faruqee and Laxton (2000) and Faruqee (2002) introduce the population growth dynamics into the model. The basic law of motion for the population is given by:

$$\frac{\dot{N}(t)}{N(t)} = n(t) = b(t) - p(t) \tag{4.1}$$

where N is the level of the population, n is the population growth rate, $b(t)$ and $p(t)$ are the economy-wide birth rate and death (mortality) rate[5]. They are time-varying,

[4]The young dependent without any income would also cause the discontinuity problem. However, in this stylized model, we don't consider the young, thus new born agents would enter the labor force and earn wages immediately.

[5]Given constant death rate p, the numbers of the cohort born at time s and

age-invariant exogenous variables. Since the youth are ignored in this model, the birth rate is the arrival rate of the labor force. In the simulation, percentage of the 20 year cohort to population above age 20 is used as the birth rate. If equation (4.1) is integrated over time, the size of the total population at time t is given by:

$$N(t) = e^{\int_{-\infty}^{t} n(v)dv} = e^{\int_{-\infty}^{t} [b(v)-p(v)]dv} \tag{4.2}$$

Equation (4.2) shows that total population evolves according to the accumulation of past changes of the growth rates.

2. Dependency Ratio

It is useful to define measures that characterize the age distribution of the population to study demographic issues. First, total population could be derived by aggregation, which is the summation of all existing individuals across all cohorts (indexed by s):

$$N(t) = \int_{-\infty}^{t} N(s,t)ds = \int_{-\infty}^{t} b(s)N(s)e^{\int_{-\infty}^{t} p(v)dv}ds \tag{4.3}$$

where $N(s,t)$ is number of existing individuals born at time s (Cohort s) and survived at time t. Then we can define the elderly dependency ratio[6] as the proportion of the total population above a certain age as follows:

$$\phi(t) = \int_{-\infty}^{j(t)} \frac{N(s,t)}{N(t)}ds; \qquad 0 < \phi < 1 \tag{4.4}$$

where $j(t)$ is the threshold level. For example, if $j(t) = t - 45$, and let $t = 2000$, then $\int_{-\infty}^{t-45} N(s,t)ds$ is the number of individuals who were born before year 1955 and were

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survived at time t is given by $N(s,t) = b(s)N(s)e^{p(t-s)}$.

[6]In this model, the elderly dependency ratio is defined as proportion of elderly population to total population. However, conventionally elderly dependency ratio is defined as elderly population to the working population.

still living in year 2000. Hence $\phi(t)$ is the proportion of individuals aged 45 above to total population[7].For the case where the birth rate and death rate are time varying, the dependency ratio evolves over time according to:

$$\dot{\phi}(t) = \frac{N(j(t),t)}{N(t)} - [p(t) + n(t)]\,\phi(t) \tag{4.5}$$

The change in the dependency ratio is determined by the relative size of new dependents crossing the threshold age, less the proportion of the elderly who die ($p\phi$) and accounting for growth in the population base ($n\phi$).

3. Age-Earning Profiles

The introduction of the age-earning profiles by Faruqee (2002) enables demographics to affect the economy in aggregate level. The age-earning profiles indicate that the labor income initially rises with age and experience, before eventually declining with retirement. This hump shaped age-earning profiles could be treated as an hump shaped effective labor supply with a same wage rate for all cohorts at any time of their life, where the effective labor supply for any individual rises with age and experience, reaches the peak in his late middle age and then declines gradually for the rest of the life. The hump shaped effective labor supply $l(s,t)$ for cohort s at time t could be approximated and calibrated by the following equation:

$$l(s,t) = a_1 e^{-\alpha_1(t-s)} + a_2 e^{-\alpha(t-s)} + (1 - a_1 - a_2)e^{-\alpha_3(t-s)}; \quad t \geq s \tag{4.6}$$

The first two exponential terms could represent the decline in an individual cohort's labor supply over time as it ages. The third term could be interpreted as reflecting

[7]I don't consider young population under age 20 in this model. So individuals aged above 45 are people aged 65 above in the real world.

gains in earnings that accrue with age and experience[8]. The parameters of as and αs could be estimated by non-linear least square with real data. The shape of the curve is the same for all cohorts and constant over time in this model. Given a wage rate $w(t)$, the individual labor income is given by:

$$y(s,t) = w(t)l(s,t) \tag{4.7}$$

Thus, $y(s,t)$ reflects the individual age-earning profiles which has a similar hump shape with observed data.

The total labor income can be obtained by integration of all individuals, which represents a bottom-up aggregation.

$$Y(t) = \int_{-\infty}^{t} y(s,t)N(s,t)ds = w(t)L(t) \tag{4.8}$$

Where L is aggregate effective labor supply. The hump-shaped profiles thus will affect the economy in both supply and demand. Changes in demographics in turn will significantly affect the macroeconomic outcomes.

Based on the definition of individual effective labor supply in (4.6), total labor supply can be written as summation of three components, $L_1 + L_2 + L_3$. In the presence of demographic dynamics, the law of motion of the aggregate effective labor supply is given by:

$$\begin{aligned} \dot{L} &= \dot{L}_1(t) + \dot{L}_2(t) + \dot{L}_3(t) \\ &= b(t)N(t) - (\alpha_1 + p(t))L_1(t) - (\alpha_2 + p(t))L_2(t) - (\alpha_3 + p(t))L_3(t) \end{aligned} \tag{4.9}$$

Intuitively, the change of the aggregate effective labor supply is determined by the new entrants to the labor force less the death among existing workers.

[8]The coefficient of the third term is $1 - a_1 - a_2$, reflecting a normalization that the youngest cohort earns income equal to unity.

4. Consumption

Denote real consumption, non-interest income, nonhuman wealth or financial wealth, and human wealth of an agent born at times s as of time t by $c(s,t)$, $y(s,t)$, $a(s,t)$ and $h(s,t)$. If let the "real" is defined in terms of the tradable good, then $c(s,t) = c_t(s,t) + c_n(s,t)/\varepsilon$[9] and $y(s,t) = y_t(s,t) + y_n(s,t)/\varepsilon$, where subscription t refers to tradable and subscription n refers to non-tradable. Let r be the interest rate, same as the world's interest rate which is constant over time and let death rate p be constant over time for a simplified case. Under the assumption that instantaneous utility is logarithmic and separable Cobb-Douglass utility across tradable and non-tradable good, the agent maximizes

$$E_t \left\{ \int_t^{\infty} \log \left[c_n^{\gamma}(s,v) c_t^{1-\gamma}(s,v) \right] e^{(\theta+p)(t-v)} dv \right\}, \quad \theta \geq 0 \tag{4.10}$$

If an individual has wealth $a(s,t)$ at time t, he receives $ra(s,t)$ in interest and $pa(s,t)$ from the insurance company. Then a simplified version of the dynamic budget constraint is

$$\dot{a}(s,t) = (r+p)a(s,t) + y(s,t) - \tau(s,t) - c(s,t) \tag{4.11}$$

where $y(s,t) = y_t(s,t) + y_n(s,t)/\varepsilon$, $c(s,t) = c_t(s,t) + c_n(s,t)/\varepsilon$ and $y(s,t) - \tau(s,t)$ is disposable labor income. After taking the Hamiltonian and solving the maximization problem analytically, the solution is given by

$$c(s,t) = (p+\theta)\left[a(s,t) + h(s,t) \right] \tag{4.12}$$

[9] If all real variable is expressed in terms of tradable good, then we have $p_t c(s,t) = p_t c_t(s,t) + p_n c_n(s,t)$, which is equivalent to $c(s,t) = c_t(s,t) + c_n(s,t)/(p_t/p_n)$. If normalize the world price to one, above equation becomes $c(s,t) = c_t(s,t) + c_n(s,t)/\varepsilon$.

and

$$c_t(s,t) = \frac{1-\gamma}{\gamma\varepsilon} c_n(s,t) \tag{4.13}$$

where θ is the rate of time preference and $h(s,t)$ is the human wealth which equals to the present value of future labor income[10][11]. Equation (4.12) suggests that individuals build up financial wealth $a(s,t)$ to ensure a certain level of retirement consumption. Unlike traditional life-cycle models, in which elderly dis-save after retirement causing a large negative saving rates among retirees, individuals in this model will attain a certain level of financial wealth as a precaution due to the uncertainty of death.

Denote aggregate variables by uppercase letters. The relation between any aggregate variable $X(t)$ and an individual counterpart $x(s,t)$ is given by

$$X(t) = \int_{-\infty}^{t} x(s,t) p e^{p(s-t)} ds$$

Then the total consumption can be expressed as a function of aggregate financial

[10]For fixed real interest rate and death rate, individual human wealth can be written as:

$$h(s,t) = \int_{t}^{\infty} \left[y(s,v) - \tau(s,v) \right] e^{(r+p)(t-v)} dv.$$

[11]For the case of isoelastic utility functions, which is used in the simulation, given by

$$\begin{aligned} u(c) &= \frac{c^{1-\sigma}}{1-\sigma}, \quad \sigma \neq 1, \\ &= \log c, \quad \sigma = 1. \end{aligned}$$

The solution will be

$$\begin{aligned} c(s,t) &= [\Delta(t)]^{-1} \left[a(s,t) + h(s,t) \right] \\ \Delta(t) &= \int_{t}^{\infty} e^{\sigma^{-1}[(1-\sigma)(r+p)-(\theta+p)](v-t)} dv. \end{aligned}$$

wealth A and aggregate human wealth H:

$$C(t) = (\theta + p)\left[A(t) + H(t)\right] \tag{4.14}$$

where A consists of domestic equity and bonds holdings and net foreign assets: $A \equiv K + B + F$. Now the aggregate human wealth reflects the present value of economy-wide labor income streams. The law of motion for the aggregate human wealth can be characterized as follow:

$$\dot{H}(t) = \frac{\mathrm{d}}{\mathrm{d}t}\int_{-\infty}^{t} h(s,t)N(s,t)\mathrm{d}s = h(t,t)b(t)N(t) + r(t)H(t) - [Y(t) - T(t)] \tag{4.15}$$

Where T is the labor tax.

Equation (4.9) and equation (4.15) summarize how demographic dynamics affect the economic behavior through both supply side and demand side channels. On the supply side, demographic changes alter the population structure, affect the aggregate effective labor supply. On the demand side, aggregate human wealth determined by the life-cycle income and demographic structure, will affect the aggregate consumption and saving behavior.

5. Pension System

A simple pension system with lump-sum transfer scheme can be introduced into the framework as follows:

$$tr(s,t) = \begin{cases} -\alpha(t) & s > j(t) \\ +\beta(t) & s \leq j(t) \end{cases} \tag{4.16}$$

Younger generations pay the transfers $tr(s,t)$ into the system while elderly receive the benefit. The scheme is financed by payroll tax: $\alpha(s,t) = \tau_{ss}y(s,t)$. A full financing condition is required, which is $\int_{-\infty}^{t} tr(s,t)N(s,t)ds = 0$. In this particular case, full financing can be written as:

$$\frac{\beta(t)}{\alpha(t)} = \frac{1-\phi(t)}{\phi(t)} \tag{4.17}$$

Here ϕ is the dependency ratio, but is defined as the population of elderly over the total population. Thus the right hand side of above equation is the supporting ratio, which equals the benefit-to-contribution ratio. If full-financing is not satisfied, in the case of a shortfall, the deficit in social security would be closed by tax or government borrowing. The dynamics of the aggregate human wealth in the presence of social security would be modified as follows:

$$\dot{H}(t) = h(t,t)b(t)N(t) + r(t)H(t) - [Y(t) - T(t)] - \int_{-\infty}^{t} tr(s,t)N(s,t)ds \tag{4.18}$$

Now the equation includes the current financing gap from the pension system. The effects of pension system on human wealth would be zero if it is fully financed, otherwise aggregate human wealth would be affected.

6. Internal Sector

The production functions are of the Cobb-Douglas form of capital and effective labor supply for both non-tradable and tradable goods. To simplify the derivation in this stylized model, we assume all the parameters are same across the two production functions[12]. Thus we can assume that this economy only has one firm, but the productions go to different sectors, and they can not be substituted.

It is assumed that domestic firms could freely borrow at the world real interest rate in making their investment decisions. The investment decision can be derived

[12] Assuming different parameters across the functions will definitely seem more reasonable. However, all these parameters themselves are chosen based on assumptions and the results will not be far from the cast that let the parameters be constant across two functions.

as:

$$I = [q - 1 + \delta]K \tag{4.19}$$

Where I is gross investment excluding installation costs, K is domestic capital stock, δ is the rate of depreciation of capital and q is the Tobin's q, measuring the value of an additional unit of capital. The evolution of q is following the law of motion:

$$\dot{q}(t) = (r + \delta)q(t) - f'(K(t)) - \frac{I(t)}{K(t)}\left[q(t) - 1\right] + \frac{1}{2}\left[q(t) - 1\right]^2 \tag{4.20}$$

And the capital accumulation or the net investment is based on following function:

$$\dot{K} = I - \delta K \tag{4.21}$$

According to equation (4.19), domestic investment is independent of domestic saving and consumption behavior, because of the mobility of capital for the small open economy case[13]. Thus the investment rule is separable from the consumption behavior (Fisherian separability).

Government spending is assumed to have the same ratio with consumption between tradable and non-tradable goods. That is:

$$G_t(t) = \frac{1 - \gamma}{\gamma\varepsilon} G_n(t) \tag{4.22}$$

Where G_t and G_n are the government spending on tradable and non-tradable goods. Total government expenditures G are financed either trough taxation T or the issuance of government debt B. Thus the law of motion of debt is given by:

$$\dot{B} = rB + G - T \tag{4.23}$$

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[13]From the policy prospective of China, free mobility of capital is not allowed. However, in fact, it seems that you can always find a way to invest or withdraw.

Finally, the non-tradable good market clearing is given by:

$$Y_n(t) = C_n(t) + G_n(t) \tag{4.24}$$

Non-tradable good market is cleared at any time t. There is no substitution between non-tradable and tradable goods.

7. External Sector

Current account is determined by the national accounting identities. First, national income GNP is defined as GDP Y plus net interest income from abroad: $GNP = Y + rF$, where F is the foreign asset. In turn, national saving S is determined by GNP less consumption: $S = GNP - C - G$.

In terms of external balance, the trade balance is given by the difference between domestic production and domestic absorption: $NX = Y - C - G - I$, where NX is the net export. Then current account can be calculated as net export plus net interest income of foreign asset, which in turn equals the difference between national saving and investment:

$$CA = NX + rF = S - I \tag{4.25}$$

Current account must also close the gap between national income and expenditure through international borrowing or lending, it also equals the changes in the stock of net foreign assets:

$$CA = \dot{F} \tag{4.26}$$

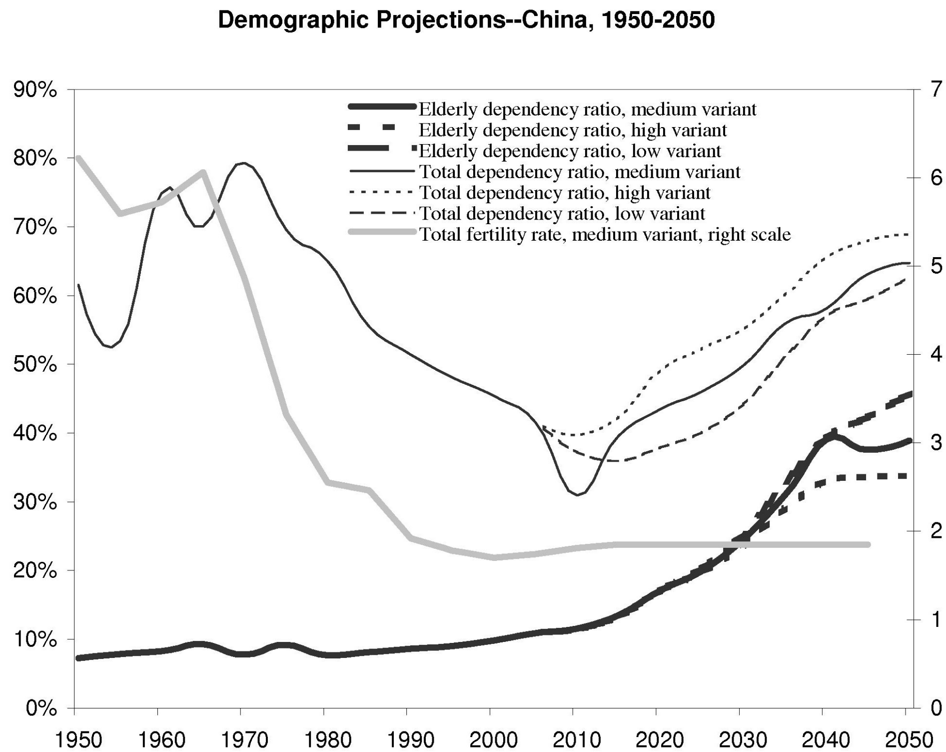

Fig. 6. China Demographic Projections

C. The Data

The raw demographic projections used in this chapter is from United Nations (UN) data set[14]. UN projects the demographic movements up to year 2050 and has three scenarios or variants named by UN. They are low variant, medium variant and high variant cases respectively. The three variants can be seen as different opinions or assumptions for the demographic changes. Low variant case assumes a low total

[14]World population prospects: the 2004 revision population database. http://esa.un.org/unpp/. Another source of data is from the World Bank. http://genderstats.worldbank.org/hnpstats/. However I think the assumption for the projection is not as good as that by UN.

fertility rate (TFR). TFR is defined as the average number of children a woman have during her life time. A higher TFR may imply a higher birth rate and a higher population growth. The number 2.1 of TFR is the replacement rate for the population. Population will be constant, growing and declining if the TFR equals, is greater or is less than 2.1 respectively. Thus a number less than 2.1 may implies the population is aging. Medium variant and high variant assume a normal and high TFR respectively.

Figure 6 presents the historical data and UN projections on demographics of China till year 2050. The thick dark line is the elderly dependence ratio. The divergences of this line after year 2010 represent the three variants (scenarios). The thin dark line is the total dependence ratio, and divergences after year 2010 also represent the three variants made by UN. The thick gray line presents the total fertility rate of China. The projection part of this line is based on the medium variant case.

The total fertility rate of China dropped dramatically from above 6 at year 1970 to 1.85 at year 2000. Then UN projects the TFR at the medium variant be constant at 1.85 from year 2010 to 2050. The high variant and low variant projections on TFR are 2.35 and 1.35 from year 2010 to year 2050 respectively. The uncommon big drop of TFR at 70s and 80s can definitely be attributed to the one-child policy, strictly implemented from year 1980. However, the one-child policy could not be solely responsible for the current low TFR anymore. Like other economies in east Asia, the growth of the economy, the increase of living standard and severity of the competitiveness delay the time of having the baby for those young working professionals in the urban area. The pressure of having a baby even spreads to the rural area in China where people always tend to have more babies regardless of the strict policy. The current young population of China who grow as the only child in their family, seems reluctant to be married and have baby, which is making the aging problem even worse. The official announcement of the TFR of China is about 1.80 at year 2000, however, the number in the Statistical Year Book of China at 2000, which comes from the fifth census of China implemented at year 2000, is only 1.42[15]. The official adjust this number to 1.8 by considering unreported births in rural area. I believe this adjustment seems a little bit large. In this case, the medium variant case by UN may even be overestimated, and I will look at the results on both low and medium variants seriously.

The elderly dependency ratio in Figure 6 is defined as the ratio of elderly population (age above 65) to the working population (age between 20 and 65). Despite the sharp decrease of the total fertility rate at the 70s and 80s, elderly dependence ratio remains stable for the past 50 years. However, the medium variant projection shows that the elderly dependence ratio will increase from slightly above 10% at year 2005 to above 40% after year 2040. China is aging at a remarkable speed. This fast aging may well affect the whole economy. The low variant and hight variant projection show the elderly dependence ratio will reach its peak at about 35% and 50% at year 2050 respectively.

Usually elderly dependence ratio is used to measure the aging degree of a economy. The reason is that the aging degree as well as the elderly dependency ratio shows the relative number of non-working population to the working population. In another way, this ratio measures the burden of the economy. From this point view, the total dependence ratio, which is the summation of young dependence ratio (population aged 20 below to the working population aged between 20 and 65 in Figure 6) and elderly dependence ratio should be equally important to the elderly dependence ratio. Figure 6 show that the total dependence ratio decrease in the same manner with the decrease of total fertility rate. Total dependence ratio decrease from about 80% at year 1970 to about 40% at year 2000. This continues large decrease of total

[15]An recent article claims that this number is 1.22 by fifth census in China.

dependence ratio may be one of the reasons that help boost the China economy in the past 20 years. Projection of total dependence ratio implies that it will continue to decrease for about 10 years and then rise back to above 60% in year 2050 for the medium variant case. Both elderly dependence ratio and total dependence ratio indicate that unlike other advanced economies, China still not experiences the aging process and a serious aging problem is right ahead its way.

The World Bank also has its own projections on the demographics of China, and notably with a longer projection periods: up to 2090. However, projections from World Bank assume a not reasonably high total fertility rate, the UN data are used in this research.

Based on the setting up, it is the birth and death rate that are finally used as exogenous inputs to the model. Thus the series of birth rate and death rate from year 1950 to 2200 are constructed. The birth/death rates before 2005 are constructed from the true data, the rates before 2050 are constructed from the projections by UN, and then the birth and death rates are forced to gradually converge to a constant number for the last 100 years of simulation. The convergence of the two rates implies that the economy will converge to a steady state in the long run and is required by the simulation technique in order to let the simulation work. Also, departed from the real world, since agents immediately enter the labor market right after they are born in this model, the birth rate in the model will be the ratio of population aged 20 to the total population. The final birth and death rates used in the simulation are constructed to let the constructed data match the projected elderly dependence ratio by UN. Since the total dependence ratio is equally important, I also construct the birth and death rate to match the projected total dependence ratio by UN to serve as a robustness check.

D. The Simulation

The simulations are performed based on the following frame work. First, a baseline scenario is simulated. The baseline scenario reflects the long run steady state of the economy. Under the steady state, the birth rate and death rate are constant over time, thus the population and demographic structure as well as other economic variables are constant too. Then the birth and death rates constructed from the UN projections are used as the shocks to baseline simulation and the new simulation is performed. The difference between the new simulation and the baseline simulation shows the effects of the demographic changes or demographic shocks to the economy. For example, in the baseline simulation, we assume that the population and population structure are constant at the year 2000's value, and the economy is in its long run steady state. Then the demographic projections are deviated from the long run steady state value and are used as shocks into the baseline simulation. Then the difference between the simulation of projected demographics and baseline simulation are the effects of the demographic changes to the economy.

We first use the birth and death rate constructed to match the elderly dependence ratio projected by UN as the demographic shocks. Figure 7 shows the result for the medium variant scenario. All panels are the percentage deviations from the medium variant case to the baseline simulation, which the population is fixed at the year 2000's value. The panel at the bottom right corner presents the exogenous birth and death rate used in the simulation. Under the case of medium variant, the death rate exceed the birth rate around year 2038. This implies that the total population will increase till 2038 and start to decrease. Since the birth rate decreases sharply from year 2010 to 2020 while the death rate is much lower than the birth rate, the working population is decreasing relative to the elderly population. The bottom left

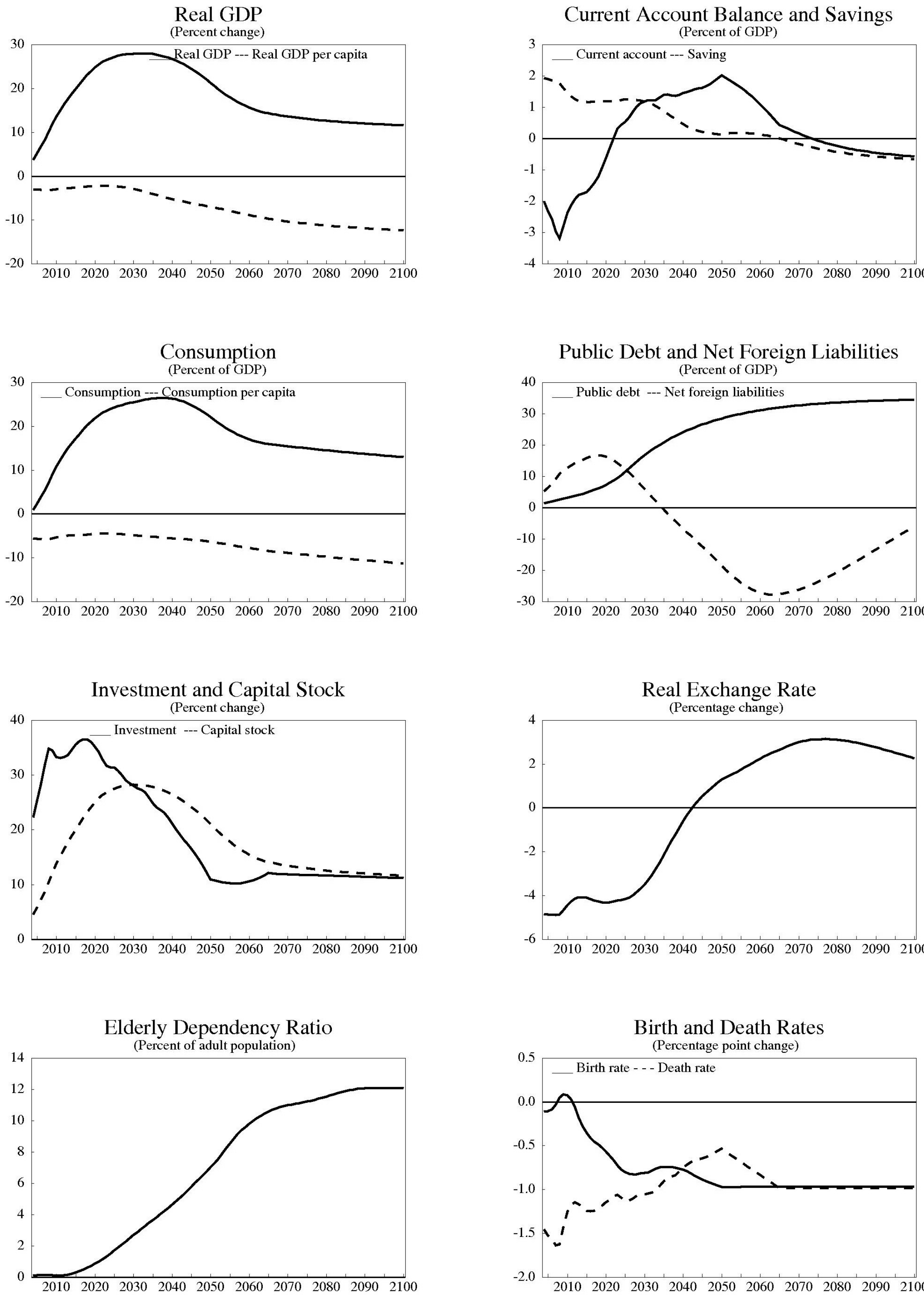

Fig. 7. Simulations for Medium-Variant, Matching Elderly Dependency Ratio

panel show the effects: the elderly dependence ratio is rising relative to the baseline scenario. At year 2100, the elderly dependence ratio will 12 percentage higher for the medium variant case than the baseline scenario, which there is no aging at all.

From the top left panel, the GDP is rising and will be about 28% higher than the no aging case around year 2038. Then the GDP starts to decline. The reason is that the population is still growing in the medium variant case and is more than the population in the baseline case, thus the GDP is increase until the point that the total population begins to decrease. However, the GDP per capita is always below the the baseline scenario. This comes from the relative position of the working population and elderly population. Although the total population is growing, because of the sharp decrease of birth rate and the mild increase of death rate, the working population increases less than elderly population increases, thus the increase in the GDP is less than the increase in the total population. This is why we observe a lower GDP per capita than the baseline scenario. In the second panel to the top on the left column, Consumption and consumption per capita exhibit similar pattern as the GDP and GDP per capita. The total consumption is higher than the baseline scenario. It increases till about year 2038 and decreases thereafter, however, the consumption per capita is always less than the baseline case where no aging problem happens.

The top right panel demonstrates the behaviors of current account and national saving. These behaviors are also rooted from the exogenously determined birth and death rate. The higher birth rate than the death rate in the near future implies that the working population is still abundant relative to the baseline case. This leads to a higher total GDP and a positive current account. The higher birth rate also implies a higher young population relative to the baseline case, and the young save little since they just joint the labor force with less earnings, the national saving rate is lower than the baseline case in the near future. As the birth rate continues to decrease and the death rate continues to increase until finally the death rate is higher than the birth rate, the current account keeps decreasing until becomes negative relative to the baseline scenario. The demand exceeds the production as the aging process moves on. The saving behaves a little different. It rises at first then decrease relative to the baseline case. This is because the abundant young population in the near future who save little at that time, enter their middle-age, which is a period that people save a lot. Finally they move into their elderly-hood and save few, making a declining national saving rate relative to the baseline case.

Finally let us look at the real exchange rate panel, locate at the second to the bottom on the right column. The real exchange rate is continuously rising from from about negative 4% to positive 3% relative to the baseline scenario. The reason is the same. At the beginning, the proportion of the young population with more effective labor supply is higher than the case of baseline, this implies a lower real exchange rate. However, this situation becomes worse and worse and finally the proportion of elderly population with less effective labor supply becomes higher than the baseline case. Thus the real exchange rate keeps appreciation.

Figure 8 demonstrates the simulation result for the case of low variant scenario. As discussed earlier, although the medium variant assumes a 1.85 total fertility rate, which is close to the official announcement of 1.80 for year 2000; however, the low variant case which has a total fertility rate of 1.35 may be close to the real situation of China. All panels have similar patterns to the corresponding panels in Figure 7, but are different in magnitudes. The origin for these differences is from the differences in birth and death rate. From the birth/death rates panel in the bottom right corner, we can observe that the death rate exceeds the birth rate at around year 2030, which is about 10 years earlier that the medium variant case and the death rate increases faster in the low variant case. This low fertility rate finally leads to a lower GDP and

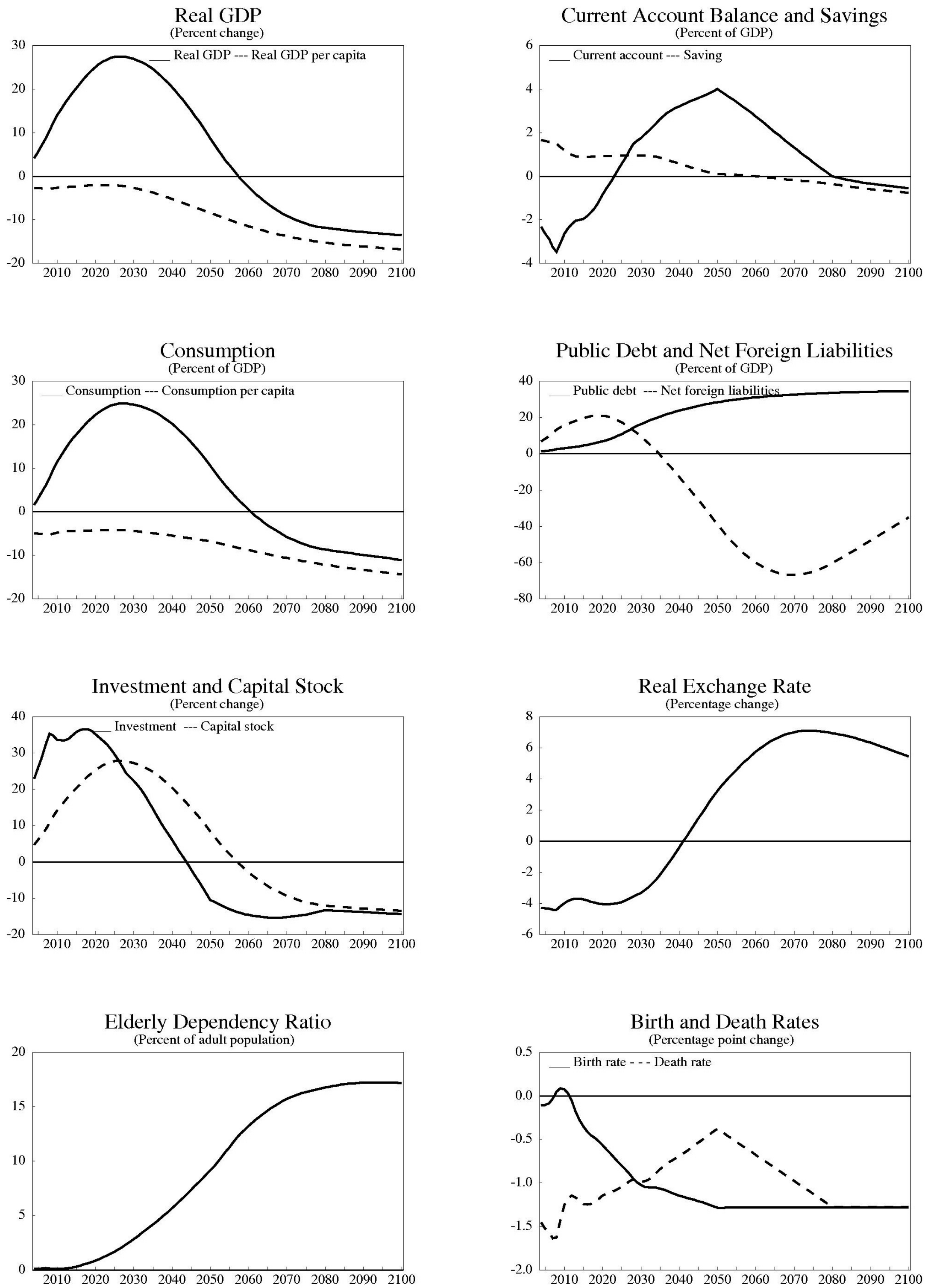

Fig. 8. Simulations for Low-Variant, Matching Elderly Dependency Ratio

Consumption than the baseline scenario in the long run. Recall that for the medium variant case, only the GDP/Consumption per capita are lower than the baseline case not the GDP and Consumption. In this case, the elderly dependency ratio will be about 18 percentage higher than the baseline case, 6 percentage than the medium variant case. Finally we observe a much higher real appreciating in exchange rate.

However, the baseline scenario, in which the population is fixed at year 2000 level, may not be good. In this case, Figure 9 plots the difference between high variance case and low variant case. The basic assumption for high variance case used by UN is that the total fertility rate is assumed to be 2.35, a little bit higher than the replacement rate of 2.1. In Figure 9, the death rate always equals or is greater than the birth rate. Thus the GDP and Consumption in low variant case are almost always less than the high variant case as well as the per capita value. And the real exchange rate in low variant case is almost 7% higher in peak than the case of high variant.

Note that the model in this chapter only consider the adult population, namely the population above 20 year old and the new born will join the labor force immediately. For example, population of 1 year old in the model is the population of 21 years old in the real world. In this case, the exogenous birth and death rate used in model simulation are revised and constructed to match the UN projections on future demographics of China. In simulation results presented in Figure 7 to Figure 9, the birth and death rates in the model are constructed to match the elderly dependence ratio, projected by UN.

However, the total dependency ratio is also important to look at. Dependency ratio tells us the burden of the working population. Elderly dependence ratio only shows the burden implied by elderly population. While the truth is that the working population also bear the burden from the young dependent. The total dependence

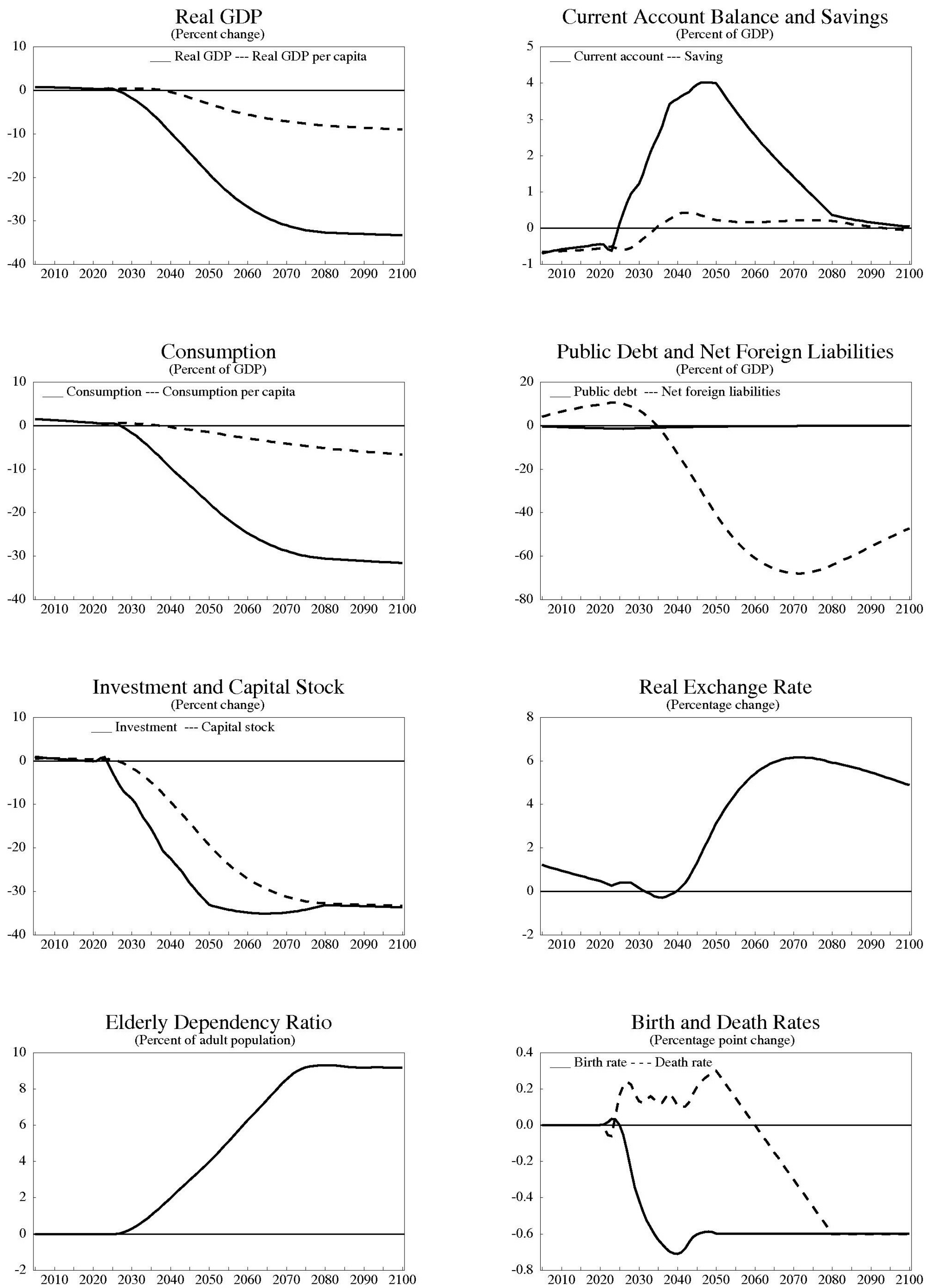

Fig. 9. Difference between High and Low-Variant, Matching Elderly Dependency Ratio

ratio clearly demonstrates the full burden of the working population. Let us revisit Figure 6. The dependence ratio is quite flat over the past 40 years and rise sharply from now. This implies that China is aging and working population will bear more and more burden in the future 40 years. The elderly dependence ratio and total dependence ratio might be much alike for other economies, however they are quite different in China. This is the first reason that we need to consider the total dependence ratio. The burden story is dramatically different when we look at the total dependence ratio for China. By including the young dependence ratio, the burden in raising the young, Total dependence ratio is as high as about 75% at 70s, declines sharply to about 30% until year 2010 and then rise back to about 65% till year 2050.

The second reason to look at the total dependence ratio is that this number might be quite important to the economy. China begins the economic reform from about year 1980. Everyone tends to attribute the great economic development of China for the past 25 years to this economic reform. But I would like to argue that the demographic changes may well play a role. The sharp decrease of the total dependence ratio may support the economic development of China a lot. Also note that the nominal exchange rate of China decreases for the past 25 years. This may be partly explained by the movement of the total dependence ratio, or to be exact, the movement of demographics. So in this research, I also construct the birth and death rate to match the total dependence ratio projected by UN. The next three figures demonstrates the simulation results.

Being the same pattern with previous three figures, Figure 10 shows the simulation results for medium variant case, but the birth and death rates are constructed to match the total fertility rate. Figure 11 presents the low variant case and Figure 12 demonstrates the difference between high variant case and the low variant case.

In both Figure 10 and Figure 11, the death rate exceed birth rate at least 10

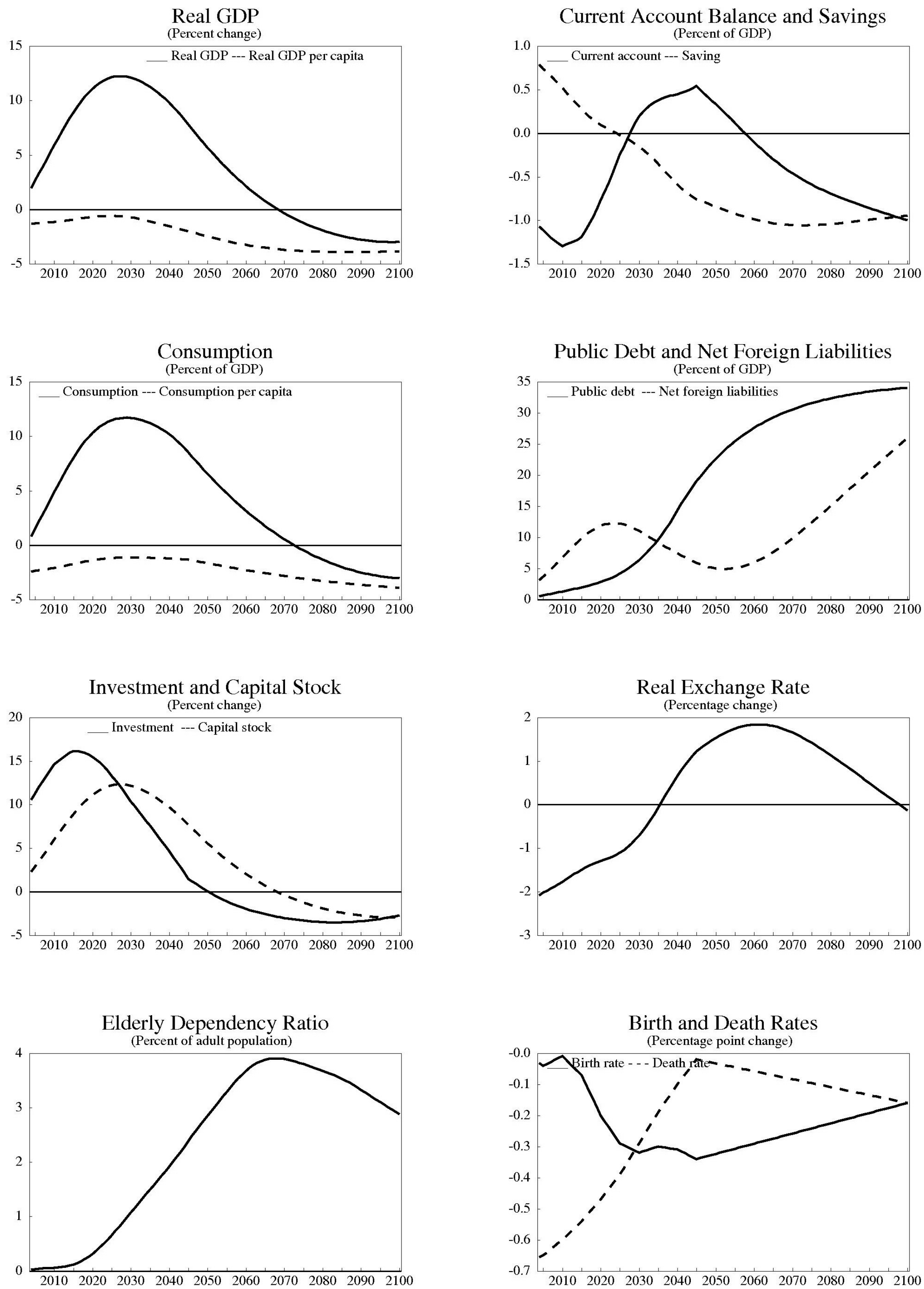

Fig. 10. Simulations for Medium-Variant, Matching Total Dependency Ratio

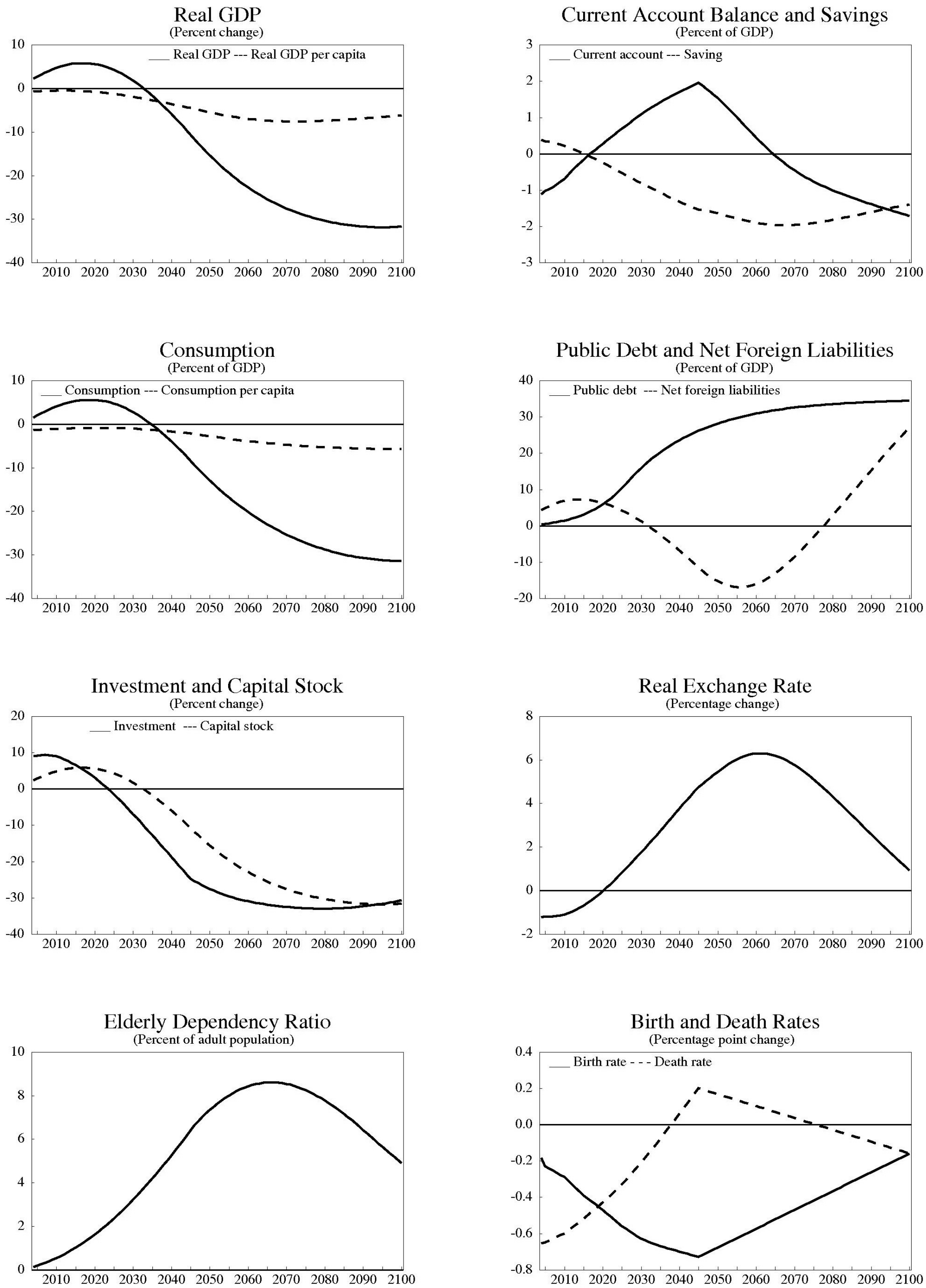

Fig. 11. Simulations for Low-Variant, Matching Total Dependency Ratio

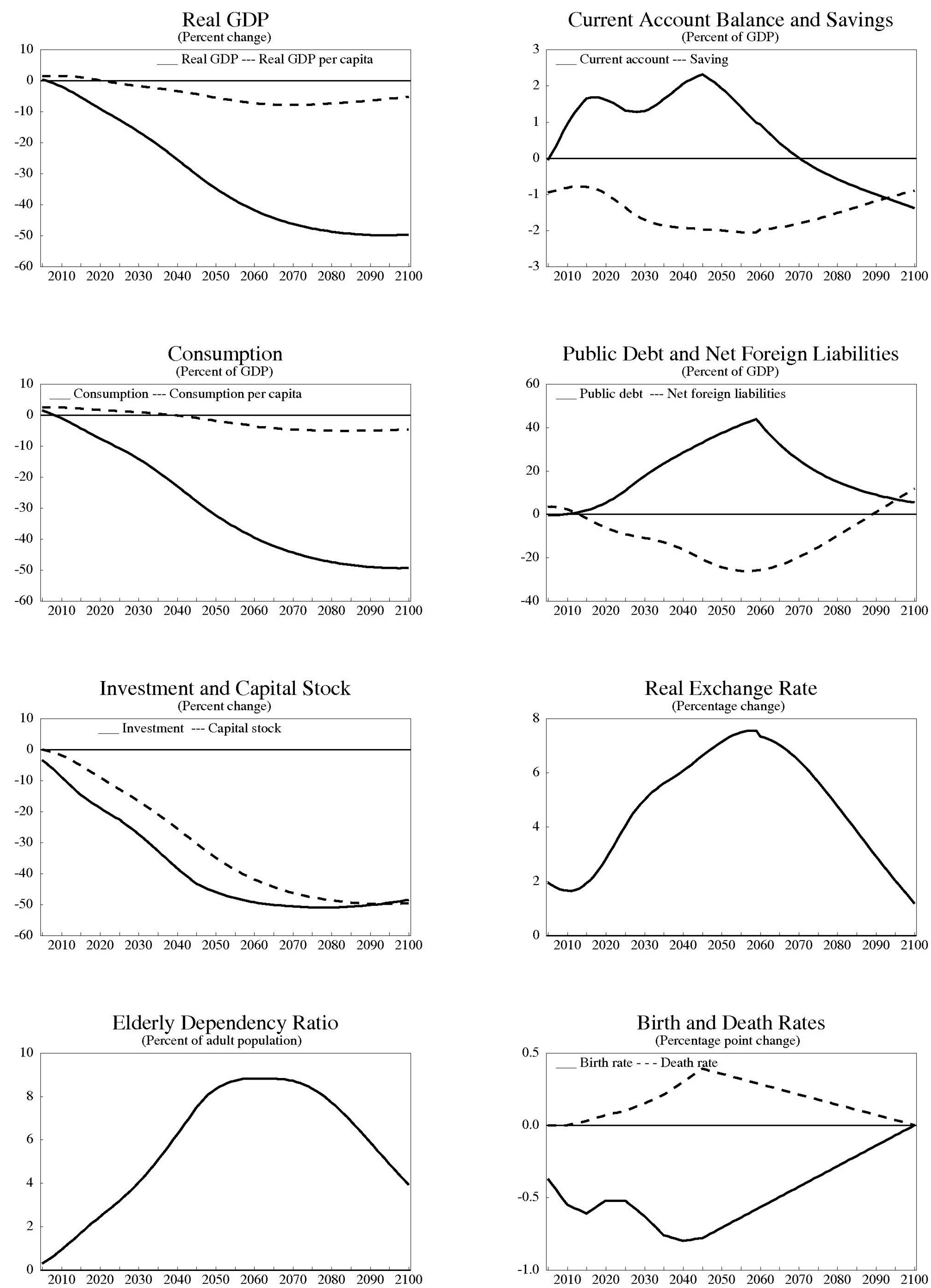

Fig. 12. Difference between High and Low-Variant, Matching Total Dependency Ratio

years earlier than their counterpart in Figure 7 and Figure 8. This makes GDP and Consumption in Figure 10 be less than the baseline scenario in the long run, opposed the GDP and Consumption in Figure 7. Since in terms of total dependence ratio, the working population will bear more and more burden at a much earlier stage, GDP and Consumption in Figure 11 (the low variant case) become less than the baseline scenario much faster and decrease a lot after that. Both will be more than 30% less than the baseline scenario at year 2100. However, since the differences in percentage between the birth rate and death rate are smaller in both medium and low variant cases, when the birth and death rate are constructed to match the total fertility rate, the aging effects are less severe in Figure 10 to Figure 12. For example, in Figure 11, the case of low variant, the GDP per capita is about 6% less than the baseline scenario in the long run, while the it is about 17% lower than the baseline scenario in Figure 8 (the case of low variant, the birth and death rates are constructed to match the elderly dependence ratio only). Real exchange rate shows similar pattern. There will be a real appreciation in exchange rate in the future. However, since the birth rate exceed death rate at a very early stage and converge gradually, the real exchange rate depreciates in the late of 21th century after an appreciation.

E. Conclusion

Similar to many countries around the world, China is undergoing significant demographic changes as its population is aging. Unlike western economies and other developed economies in Asia, China will become aged before she gets rich. China is also in the midst of the great economic transition. China is steadily moving toward a more liberalized market and becomes more and more open to the international trades. Demographics is one of the key factors that affect the economy in the long run. In this research, I look at how the demographic change in China will affect her real exchange rate.

Following Tamirisa and Faruqee (2006), I use a dynamic overlapping generations model of a small open economy, incorporated with demographic and life-cycle dynamics based on Faruqee (2002). I extend this model by including a non-tradable sector to introduce the dynamics of real exchange rate. I use the future population path projected by UN as the exogenous input to the model and simulate. The Simulation results indicates that exchange rate of China will have a real appreciation in the foreseen future. Another important finding is that both GDP per capita and consumption per capita in China will be lower than the case without aging problem.

CHAPTER V

CONCLUSION

Chapter II investigates the relation of trading volume and price movements. It is generally believed that a large price change is often associated with large trading volume. As the old Wall Street adage says: "It takes volume to make prices move." As trading volume plays such an important role in the price adjustment process, we can utilize this information to gain further understanding of price changes.

I propose a model to explain the dynamics of price and trading volume. Because it is hard to find an analytical solution for this model, I use simulation methods. A trading platform, Mini-Exchange, is developed using Matlab. There are indeed many theoretical models being developed to study microstructure of financial market, but too many not-so-realistic assumptions have been made to solve the model. This exchange platform provides a brand-new approach to solve the theoretical model. Traders simply generate their limit orders based on this model, and submit these orders to the Mini-Exchange to trade.

Simulation results demonstrate similar pattern to those we see in real-world stock prices movements displayed in Figure 1. The trading volume is relatively low at beginning or during the price adjustment process. Regression analysis by Zou (2007) on several large company stocks shows that trading volume indeed has some prediction power for price movements.

Chapter III studies the martingale behavior of growth and value style indexes as well as general stock market indexes for thirteen major international stock markets. In addition to the linear model, I also employ several popular nonlinear models to capture potential nonlinearity-in-mean in stock returns. I find that growth stock portfolios appear to be more predictable than value stock portfolios as well as the general stock market indexes. By contrast, there is no clear evidence that value stock portfolios are more predictable than the general stock markets. To the best of my knowledge, this result is novel.

Consistent with early authors, e.g., Leitch and Tanner (1991), Hong and Lee (2003), and Campbell and Thompson (2005), I emphasize the importance of using economic criteria, in addition to commonly used statistical criteria in the forecast evaluation. Such consideration appears to be crucial to the main finding of this study. In particular, while statistical criteria fail to reject the martingale hypothesis for all the growth stock price series except one country, economic criteria suggest predictability of the direction of price changes as well as trading returns for nine countries.

In Chapter IV, I look at the effects of the demographic changes in China on her real exchange rate. Similar to many countries around the world, China is undergoing significant demographic changes as its population is aging. Unlike western economies and other developed economies in Asia, China will become aged before she gets rich. China is also in the midst of the great economic transition. China is steadily moving toward a more liberalized market and becomes more and more open to the international trades. Demographics is one of the key factors that affect the economy in the long run. In this research, I investigate the linkage between demographics and exchange rate in China.

Following Tamirisa and Faruqee (2006), I use a dynamic overlapping generations model of a small open economy, incorporated with demographic and life-cycle dynamics based on Faruqee (2002). I extend this model by including a non-tradable sector to introduce the dynamics of real exchange rate. I use the future population path projected by UN as the exogenous input to the model and simulate. The Simulation results indicates that exchange rate of China will have a real appreciation in the foreseen future. Another important finding is that both GDP per capita and consumption per capita in China will be lower than the case without aging problem.

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