Ph.D Dissertation

Essays on the Dynamics and Cross-Section of Stock Returns

— To strength the understanding of the driving forces and information in asset prices —

Chen Sichong

January 2010

To my parents ...

for teaching me the value of knowledge;

To Xiaowei ...

for her constant support and encouragement;

To Ruoyu ...

for giving me the chance to take care of.

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Chapter 1

Motivations

Why am I interested in the dynamics and cross-section of asset prices? It simply because I think it is an important and urgent task in macroeconomics and finance to sharpening our understanding of the dynamics and cross-section of asset prices. Therefore, My thesis title follows. The paragraphs in this section discuss some reasons briefly and introduce you to my work.

My research interest begins with a still ongoing debate about whether monetary policy should respond to asset prices other than general price levels. The ultimate goal of monetary policy is to influence the macroeconomic variables such as inflation, output, and unemployment. However, monetary policy do not has direct control over those variables. It is asset prices and returns through which monetary policy may affect economic agent's behavior to influence the macroeconomic variables. Therefore, if we want to understand the policy transmission mechanisms, we cannot avoid understanding of the link between monetary policy and asset prices. Moreover, before we discuss about whether it is desirable to respond to asset prices by using monetary policy tools, it is better for us to make it clear about how and to what extent monetary policy could affect asset prices. We should explore the economic forces driving the reaction of asset prices. In order to do so, we have to understand about why asset prices are what they are, why they are high in some time but low at the other time, why some assets could earn higher returns than others. Without a thorough understanding about the forces driving variation in asset prices, we may not be able to evaluate the effect in changes of policy action on asset prices.

More fundamentally, linking the asset pricing phenomena to macroeconomics is a central task of both macroeconomics and finance. The dominating DSGE (Dynamic Stochastic General Equilibrium) framework in macroeconomics with the real business cycle model at its core has mainly been trying to match the quantities dynamics over business cycles. In fact, most works in this line of researches have focused on quantity dynamics alone by simply ignoring asset pricing phenomena in their model, for example equity premium, return predictability, cross-sectional value effect, and so on. Unfortunately, for example, Jermann (1998) have shown that the asset pricing implication of standard business cycle models is a disaster. However, it is asset prices though which we can achieve equations in macroeconomics such as the equation of savings to investment and the equation of marginal rates of substitution to marginal rates of transformation. If the asset pricing implications are counter-factual, how can you clear markets in your model economy to derive meaningful implications for quantities. It thus remains questionable as well for their policy and welfare implications. Therefore, You need to develop general equilibrium models that account for the joint evolution of asset prices and business cycle quantities. In order to do so, you need thorough understanding of the dynamics and cross-section of asset prices.

On the other hand, we also have to understand whether asset pricing facts are linked to macroeconomic events, and how they are related with each other. We cannot look at asset prices alone and discuss the questions about whether they are "rational", or "efficient". The asset prices data alone has no information contents about the macroeconomic environments in which economic agents are trading with each other. The only way for us to answer those questions is to provide economic explanations to link asset prices phenomena to macroeconomic events. This "joint hypothesis" was stressed by Fama's original work on efficient markets several decades ago. Therefore, understanding how to interpret the dynamics and the cross-sections of asset prices have long been an important task for both macroeconomics and finance.

At an even deeper level, the use of knowledge in our society is reflected in asset prices. Changes affecting the valuation of various claims to uncertain payments are always occurring. Some are in the form of formal knowledge, while some are in the form of informal knowledge that only some individuals may perceive or observe. Like all other prices we confronted with in our consumption of goods and services every day, one of the fundamental feature of asset prices is that they summarize a huge amount of information whether they are formal and informal.

The changes of prices reflect the underlying events that constantly affect the states of the world. The states of the world are usually measured as variables that measure the overall state of economy, variables that measure the state of a corporation, or variables that forecast future state of overall economy and/or corporations, and the like. Asset prices are in this sense acting as a function that maps the states of the world into a string of observable real numbers. It is also the underlying idea to model stock returns as random variables or stochastic process.

However, we cannot usually tell what those events are. For example, the events that make the share prices of Toyota up by 100 yen may not be observable to economists or policy makers. In some cases, we even do not need to know what the underlying events are, since asset prices would guide you to do what you are expected to do as if you are armed with the full information about all the underlying events. In some other cases, such as debating about whether monetary policy should respond to asset prices, we need some thorough understanding about the underlying events that drives the changes in asset prices.

This thesis is my first attempt trying to understand the changes in asset prices over time and cross assets and markets. The following sections consist mainly five empirical works about the dynamics and cross-sections of stock returns, aiming to explore the driving forces and extract information in stock markets.

The centerpiece of modern asset pricing theory is that prices should equal expected cash flow discounted by stochastic discount factor. This present-valued framework provide a powerful organizing principle for empirical researches. It divides the underlying economic forces in financial markets mainly into two parts: one is the expected cash flow part, the other one is discounted part. Most of my work would focus on the second part about changing discount rates i.e. expected returns, or risk premia, over time and cross assets, rather than the efficient incorporation of information into asset prices. In exploring the forces driving changes over time and across assets in financial markets, our approach is empirical based on a dynamic accounting framework in a present-value form rather than behavioral models. By applying this empirical approach to financial markets, we would be able to make statements at least about the proximate causes driving the dynamic and cross-sectional changes in asset prices. The cost, however, is that we may miss the fundamental factors affecting asset prices. We still need economic models to help understand the fundamental economic reasons about the proximate causes driving asset prices. However, our empirical discoveries may help us postulate the channels and mechanisms through which we can (and should) explore (and elaborate) further to link changes in asset prices to the fundamental economic events.

On the one hand, asset pricing theory could give us an economic explanation for why prices are what they are. On the other hand, it could also provide us a way to extract the information contained in asset prices and to predict how changes in underlying variables such as policy action and economic structure would affect asset prices. If we decide that our understanding of the financial market is not bad, we can extract information from asset prices based on the existing economic theory. In doing so, we may acquire comprehensive and timely information guiding our actions to evolving problems.

I hope that the empirical discoveries presented in my thesis would contribute to our understanding about markets.

Chapter 2

The Predictability of Japanese Corporation's Equity Returns: Does Future Cash flow Matter?

2.1 Introduction

The equity market in Japan (Nikkei 225) has lost more than half of its value from mid 2007 through early 2009, with some signs of recovery recently. The volatility is also unusually high during this period. What economic forces drive the large swings in the Japanese equity market? Does it prelude further declines? Is this a signal for good prospective returns in the future? Or Does it simply reflect a gloomy outlook about future cash flow of Japanese corporations. This paper aims to provide some insights based on historical data to those questions within the framework of asset pricing theory.

Asset pricing theory tries to relate the price or value of claims to entire future uncertain cash flow stream, usually in the form of present-value statement. This present-value framework provides a powerful organizing principle for empirical researches to divide the underlying driving forces in financial markets mainly into two parts: one is the expected cash flow part, the other one is discounted part. This paper explores the implications of a dynamic accounting identity for the dynamics of equity returns in a present-value framework by using data of cash flow and market equity value of Japanese private non-financial corporations. In particular, we study the role of fluctuations in dividend yield and equity payout yield for predicting equity returns.

Valuation ratios such as dividend yield and equity payout yield are central to forecasting because they reveal agent's expectation about expected future returns and expected future cash flow which are not observable. If valuation ratios vary at all, they must mechanically come from the changing expected equity returns or cash flow or both, provided that they are stationary. In other words, the variation in valuation ratios, which is observed in the real world, means that equity returns and/or cash flow are predictable, otherwise the valuation ratios would be constant. We provide strong evidence showing that equity returns of Japanese corporations are predictable; dividend yield is a better predictor of future equity returns than equity payout yield. While the variation in dividend yield is mostly driven by changes in expected future equity returns, the variation in equity payout yield is dominated by future cash flow which incorporate equity repurchase and issuance other than dividends. Therefore equity payout yield implies smaller variation in expected equity returns.

In addition to implications about the variation in expected equity returns, our present-value framework could also provide measures to examine quantitatively the relative importance of economic forces driving the equity returns by using the forecasting results based on dividend yield and equity payout yield. In particular, we decompose equity returns into changes in current cash flow, changes in expected future cash flow and changes in expected equity returns, and compute the variance of each component to show how much variation in equity returns corresponds to changes in expected equity returns and expected changes in cash flow. Our variance decomposition result based on dividend yield shows that the variation in equity returns is dominated by changes in expected future equity returns, while the results based on equity payout yield shows that the variation in equity returns is mainly explained by changes in current cash flow. Since the two models use different sets of conditioning information, it is not surprising to see different implications for the driving forces of return variation. However, the bottom line is that either one of the two cases suggests that changes in expected future cash flow play only a small role in the variation of equity returns.

The rest of the paper proceeds as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 presents the present-value framework to decompose the dividend yield, equity payout yield and equity returns.

Section 5 reports the empirical results. Section 6 concludes and discuss the implications.

2.2 Literature

Relevant literatures have been routinely exploring the driving forces of equity markets by examining the present-value relation between dividends and equity prices. At least since the seminal works of Shiller (1981) and LeRoy and Porter (1981), who employ the variance-bound test to show that changes in future dividends are too stable to justify the movement of equity prices, economists have constantly argued that cash flow is not so much relevant to the dynamic movements of equity prices. On the other hand, Fama and French (1988) shows that equity returns are predictable in terms of dividend yield and the predictive power rises with the horizons. Since then, a large number of researches have documented that equity returns seem to be predictable in a lot of countries from many variables, especially valuation ratios like dividend yield.

Campbell and Shiller (1988) and Cochrane (1992) connect the equity price volatility to the predictability of equity returns in a log-linearized present-value framework to show that the variation in dividend yield must correspond to the changes in expected equity returns or expected dividend growth rates. They employ the variance decomposition method to show that almost all variations in dividend yields are due to changing expected equity returns rather than changes in expected future dividend growth. Campbell (1991) and Campbell and Ammer (1993) then use the dynamic accounting framework and variance decomposition approach to show that variation in unexpected excess equity returns could be in large part attributed to changing expectations of future excess equity returns.

However, a large number of works argue that it still remains unclear about the relative importance of expected equity returns and expected future cash flow in driving the equity market by questioning the the statistical significance of equity return predictability. For example, Stambaugh (1999) finds bias in the forecasting coefficients and their associated standard errors about equity returns by deriving the finite-sample distribution of forecasting coefficients, and shows that the return forecasting regressions would not be statistically significant at the conventional levels if we take the finite-sample bias into account. Goyal and Welch (2003) reports that equity return forecasts based on dividend yield do not perform well out of sample, and even sample mean would yield a better prediction than do the forecasting regressions based on dividend yield. Hodrick (1992) and Boudoukh, Richardson and Whitelaw (2008) argue that stronger evidence about the long-horizon return forecasting regressions may be an illusion, simply due to the high persistence of dividend yield. On the other hand, Cochrane (2008a) finds that the absence of dividend growth predictability and long-horizon return predictability gives stronger evidence to support the return predictability from both the economic and statistical sense.

Boudoukh, Michaely, Richardson and Roberts (2007) finds that dividend yield may experience structural changes, and argue that total (net) payout including the (net) repurchase is a more appropriate measure of cash flow. They show that total (net) payout yield instead dividend yield has statistically and economically significant predictability of equity returns. Larrain and Yogo (2008) argue that net payout, which is the sum of dividends, interest, and net repurchase of equity and debt, is an appropriate measure of cash flow for valuing corporate assets, and shows that the variation in net payout yield is mostly driven by movements in expected cash flow growth.

About the Japanese equity market, 植田・鈴木・田村 (1986) and Hoshi (1986) apply the variance-bond test to show that movements in equity prices could not be explained by changes in future dividends by holding discount rate constant. Hamao (1991) constructs a value-weighted equity price index from individual corporations listed TSE (Tokyo Stock Exchange), which is comparable to that of CRSP (Center for Research on Security Prices) in U.S., to take into account the effect of dividend. Campbell and Hamao (1992) uses this index to show that excess equity returns in Japan are predictable by forecasting variables both in Japan and U.S.. Recently, 青野 (2008) employs the variance decomposition approach to investigate the predictability of equity returns calculated from TOPIX, and concludes that variation in unexpected excess equity returns is mostly explained by changes in expected future dividend growth rather than changes in expected returns. He also shows the results are robust to structural change considerations. Chen (2008) investigates the dynamics of J-REIT equity listed in TSE by employing the Log-linearization and VAR method to decompose the excess J-REIT equity returns into changes in expected dividends, real interests and future excess returns, and finds that the news about future dividends combined with future excess returns account most of the movement of the J-REIT equity.

Our research fills the gap to provide a comprehensive analysis about the equity return predictability for Japanese corporations in general. In particular, we exploit the joint null hypothesis in which equity returns are not predictable must accompany that future cash flow are predictable. Statistical tests based on dividend growth and long-run return forecasts would give us more powerful statistics. We also take into account the possible small-sample bias by deriving the small-sample distribution of forecasting coefficients based on Monte Carlo simulations. We provide significant evidence for the predictability of equity returns of Japanese corporations, and show that dividend yield is a better predictor of equity returns than equity payout yield. In contrast to previous studies about the Japanese equity returns, we find that changes in expected future cash flow play a very small part in the variation of equity returns. This conclusion is robust whether we measure the cash flow by dividends or equity payouts.

2.3 Data

Our basic data used in the following analysis is taken from two sources: one is Annual Report on National Accounts of Japan (SNA) published by Cabinet Office, and the other one is Flow of Fund Accounts (FFA) published by Bank of Japan. In particular, the market equity values of Private Non-Financial Corporations are contained in the Assets and Liabilities Table of FFA, while data about cash flow of Private Non-Financial Corporations are recorded in the Transaction Table of FFA and Income and Outlay Accounts of Annual Report on SNA. Since data in FFA is used as basis in compiling the SNA, data from the two sources are considered to be consistent.[1] All the data are in annual frequency. The sample period is from fiscal year 1980 to fiscal year 2007 for flow data and from the end of fiscal year 1979 to the end of fiscal year 2007 for stock data.[2]

We define the gross equity return as Eq. (2.1).

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}, \tag{2.1}$$

where R, P and D denote the gross equity returns, equity prices per share and dividends per share respectively. Multiplying both numerator and de-

[1]Please see the Guide to Japan's Flow of Funds Accounts published by Research and Statistics Department of Bank of Japan for detailed reference.

[2]Data from FFA and SNA in our sample period is compiled based on 1993 SNA standard, which employs the Mark-to-Market Accounting principle to evaluate transaction items on a market value. There is no retroactive data available beyond this sample period.

nominator of the right side of Eq. (2.1) by the number of shares outstanding, we can rewrite it as Eq. (2.2).

$$R_{t+1} = \frac{V_{t+1} + DV_{t+1} + C_{t+1}}{V_t}, \tag{2.2}$$

where V, DV, C denote total market equity value, total dividends, and other equity payouts other than dividends such as repurchase net of issuance respectively. We are using Eq. (2.2) to calculate equity returns in practice.

We follow the value-weighted dividend yield of TSE to divide the total dividends for each fiscal year by the market equity values at the end of corresponding fiscal year to construct a value-weighted dividend yield series for Private Non-Financial Corporations. We divide the total equity payouts, which take into account the other cash flow such as equity repurchase and issuance other than dividends, for each fiscal year by the market equity values at the end of corresponding fiscal year to construct a equity payout yield series for Private Non-Financial Corporations.

Figure (2.1) provides an overview about how cash flow, equity returns, dividend yields and equity payout yields vary over our sample period. There are some sensible features worth noting. First, while dividends are always positive, equity payout can be negative whenever share issuance exceeds the sum of dividends and repurchase. Second, it is evident that dividend remains pretty stable throughout the 1980s and 1990s and shows some signs of rapid increase after entering the 21st century. In contrast, it is interesting to see that equity payout, which is the total cash flow to outside investors incorporating equity repurchase and issuance other than dividends, is relatively volatile, and shows the most significant shrink at the end of equity market booms of late 1980s. It indicates that Japanese corporations did finance a large amount of funds through equity issuance from the equity market possibly due to the decline of financing cost associated with the appreciating equity market. It is also reported by Larrain and Yogo (2008) that the two striking droughts in equity payout in U.S. occurred at the end of 1929 and 2000 which also correspond to the end of equity market booms. As a result, while almost all movement of dividend yield are driven by the changes of equity prices, equity payout yield may be greatly influenced by the fluctuation of cash flow. Dividend yield is more persistent than equity payout yield.

2.4 Methodology

Following Campbell and Shiller (1988), we start with the identity about one-period return in Eq. (2.1). After dividing both sides of Eq. (2.1), we log-linearize the identity of one-period return by Taylor expansion to derive a difference equation (2.3) for dividend yield as follows:

$$dp_t = r_{t+1} - \Delta d_{t+1} + \rho(dp_{t+1}), \tag{2.3}$$

where Δ denotes first difference, dp_t denotes the log of dividend yield $d_t - p_t$, and lower letters denote the log of the corresponding variables throughout the paper. All the variables are in the form of deviations from their equilibrium value. The constants in the log-linear approximation are also ignored. ρ equals $\frac{E(P_t/D_t)}{1+E(P_t/D_t)}$.

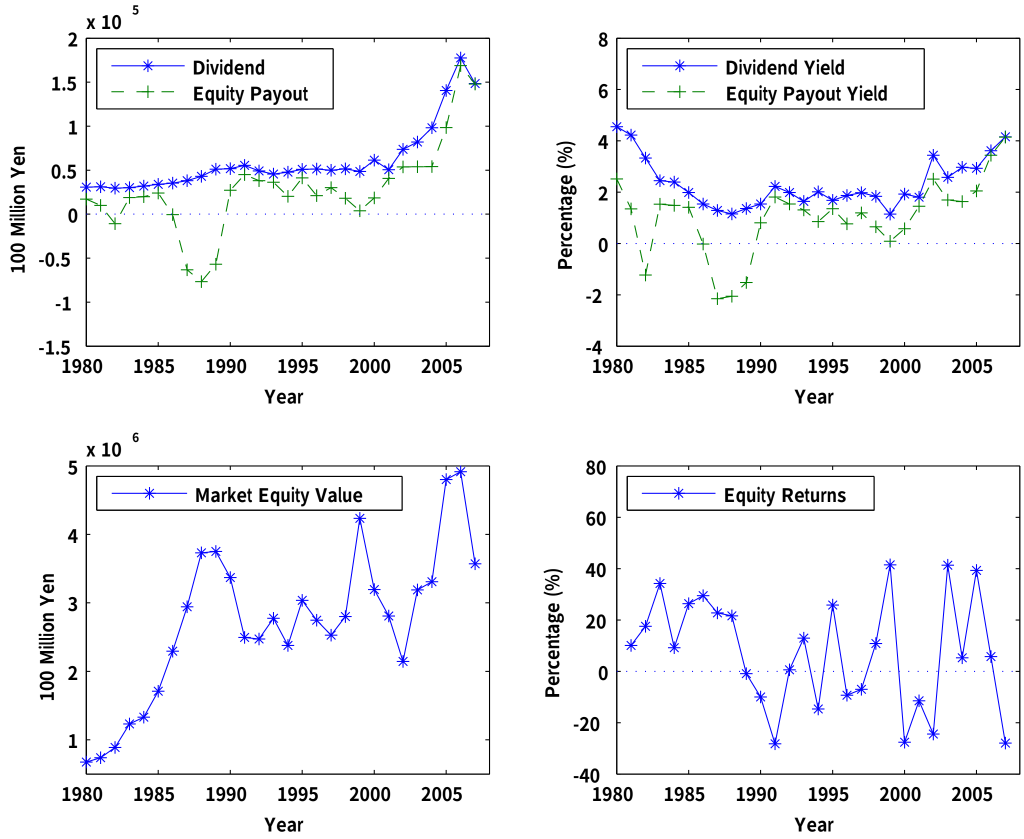


Figure 2.1: Cash flow, Market Equity Values, and Equity Returns of Private Non-Financial Corporations

We iterate the above Eq. (2.3) forward till infinite horizons to acquire Eq. (2.4).

$$dp_t = \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} - \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} + \lim_{j\to\infty} \rho^j (dp_t). \tag{2.4}$$

We are assuming that dividend yield is stationary so that the last term at the Eq. (2.4) would disappear in the infinite limit.

$$dp_t = \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} - \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}. \tag{2.5}$$

Since it is an approximated identity, the Eq. (2.5) holds ex post as well as ex ante, so that we can add expectation to express it as a present-value model of infinite discounted sum of future equity returns and future dividend growth.[3]

$$dp_t = E_t \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}, \tag{2.6}$$

where the expectation operator E can refer to any information set that includes dividend yield, e.g. investor's information set.

It is worth of noting that Eq. (2.6) says dividend yield reveals agent's expectation about expected future returns and expected future cash flow. If dividend yield varies at all, it must mechanically come from the changing expected equity returns or cash flow or both, provided that dividend yield is stationary. Since we could observe the variation in dividend yield in the real world, it means that equity returns or dividend growth or both

[3]We can derive a similar present-value model to express equity payout yield as an infinite discounted sum of future equity returns and future equity payout growth by relating market equity to equity payout.

are predictable, otherwise dividend yield would be constant. By employing variance decomposition to (2.6), we could answer quantitatively about how much variation in dividend yield corresponds to changes in expected equity returns and expected changes in future dividend growth.

In addition to implications about the variation in expected equity returns based on dividend yield, our present-value framework could also help examine the variation in unexpected equity returns. In particular, we could take expectations of Eq. (2.6) at time t and $t+1$ and take the difference to decompose the unexpected part, news, or revision in expectation of equity returns during period t to $t+1$ into three components: the changes in expectation of current dividend growth, future dividend growth and future equity returns. Note that we separate the mechanical effect of current dividend growth from the effect of future dividend growth.

$$(E_{t+1}-E_t)r_{t+1} = (E_{t+1}-E_t)\Delta d_{t+1}+(E_{t+1}-E_t)\sum_{j=1}^{\infty}\rho^j\Delta d_{t+1+j}-(E_{t+1}-E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j}, \tag{2.7}$$

where $E_{t+1}-E_t$ denotes the changes in expectation during period t to $t+1$.

Dividends may be an appropriate measure of cash flow for an investor who owns one share of a firm's equity claim. Price is the discounted present value of future dividends. However, the measure of cash flow may depend on the circumstances you consider about. There are some reasons for us to focus on other measures of future cash flow instead of dividends. Hall (2001a) have pointed out that stable dividends could be just an illusion, since securities market should discount the entire future cash flow out from corporate sector instead just dividends to securities owners. This argument is relevant when you think about a representative investor owning all the outstanding shares of corporations.

If you take a macro view to think of a representative investor who owns all outstanding shares of the firms together, the cash flow he cares about is the equity payout including dividends and net equity repurchase rather than dividends alone. The equity payout instead dividends then become a more appropriate measure of cash flow from corporations to investors. The investor who owns all the firm's equity would receive the sum of dividends and equity repurchase funds out from the firm, and invest more capital in the form of equity issuance. On the other hand, the value of a firm's equity claims owned by investors measures the market value of the firm's net worth which is the product of equity prices and the number of shares outstanding. It may be therefore desirable to examine the present-value relationship between equity value and equity payout. By studying valuation ratio based on a more comprehensive measure of cash flow to investors, we may gain important implications for the equity return predictability and the underlying forces driving equity return variations.

We follow Boudoukh et al. (2007) and Larrain and Yogo (2008) to derive a log-linearized present-value model based on Eq. (2.2) to express equity payout yield as an infinite discounted sum of future equity returns and future equity payout growth.

$$ev_t = E_t \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta e_{t+j}, \tag{2.8}$$

where ev and e represent the log equity payout yield and the log equity payout respectively.

Similar to the forecasts based on dividend yield, we would be able to decompose the unexpected equity returns during period t to $t+1$ into three terms: the changes in expectation of current equity payout growth, future equity payout growth and future equity returns. Note that we separate the mechanical effect of current equity payout growth from the effect of future equity payout growth. This decomposition help us to examine the relative importance of economic forces driving the equity returns based on equity payout yield forecasts.

$$(E_{t+1}-E_t)r_{t+1} = (E_{t+1}-E_t)\Delta e_{t+1} + (E_{t+1}-E_t)\sum_{j=1}^{\infty} \rho^j \Delta e_{t+1+j} - (E_{t+1}-E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}. \tag{2.9}$$

2.5 Empirical Analysis

2.5.1 Empirical Results based on Dividend Yield

Forecasting Regressions

We postulate a VAR(1) representation of log equity returns, log dividend growth, and log dividend yields, with log dividend yields as the only right-hand side forecasting variable to focus on the forecasts based on dividend yield.[4]

$$
\begin{aligned}
r_{t+1} &= \beta_r \cdot dp_t + \epsilon_t^r, \\
\Delta d_{t+1} &= \beta_d \cdot dp_t + \epsilon_t^d, \\
dp_{t+1} &= \beta_{dp} \cdot dp_t + \epsilon_t^{dp},
\end{aligned}
\tag{2.10}
$$

Since the approximate identity applies to each year, it allows us to derive additional identities linking the regression coefficients and errors in the VAR system according to the log-linearized identity (2.3). We thus could drop one of the redundant equation in the VAR system to infer the regression

[4]Specifying a full VAR by incorporating log returns and log dividend growth with more lags would not change results much, since the other two variables do not have much marginal forecasting power. In addition, although we could incorporate other relevant predicting variables, or find better specification about predicting equity returns, we focus on the simple forecasting regression because our objective is to provide evidence about equity return predictability based on dividend yield, rather than searching a better prediction model.

coefficients, errors and data of any equation from the information of the other equations.

Table (2.1) reports the estimation results of forecasting regressions in Eq. (2.10) of log equity returns, log dividend growth, and log dividend yields in annual frequency, with log dividend ratios as the only right-hand side forecasting variable. The sample period is from 1980 to 2008. The first row shows that return forecasting coefficients based on dividend yield is about 0.2 with t value close to 2. It indicates that higher dividend yield would forecast economically and statistically significant higher future equity returns. The second row, however, tells us that dividend yield has no predictive power about future dividend growth, since the dividend growth forecasting coefficient is not only nearly zero, but also insignificant in the statistical sense. Finally, the third row shows that dividend yield is quietly persistent with an autoregressive coefficient of 0.75.

It is often argued that there can be small-sample bias in the forecasting coefficients and their associated standard errors. Once you take the small-sample bias into account, the return forecasting coefficient may not be statistically significant. We thus derive the small-sample distribution of forecasting coefficients by Monte Carlo simulations under the joint null hypothesis in which returns are not forecastable but dividend growth is predictable, with the sample estimates of covariance matrix of forecasting regression errors.[5]

[5]Eq. (2.6) means that equity returns or dividend growth must be predictable, otherwise dividend yield would be constant. We report simulation results based on 5000 draws.

Table 2.1: Regression Results based on Dividend Yield

Panel A: Simple Forecasting Regressions

	Estimates			Error Terms		
	Coefficients	SE	t Value	r	Δd	dp
r	0.204	0.108	1.897	0.204	0.128	-0.813
Δd	-0.062	0.059	-1.061	0.128	0.137	0.471
dp	0.751	0.107	7.034	-0.813	0.471	0.238

Panel B: Long-run Regression Coefficients

	Coefficients	SE	t Value		Coefficients	SE	t Value
r	0.774	0.242	3.199	Δd	-0.237	0.245	3.115

Note: Panel (A) of this table reports the estimation results of forecasting regressions in Equations (2.10) of log equity returns, log dividend growth, and log dividend yields in annual frequency. The sample period is from 1980 to 2008. We report GMM-corrected heteroskedasticity-consistent standard errors. The diagonal of the error terms matrix are standard deviations of the regression errors, while the off-diagonal are correlation between errors. Panel (B) of this table reports that long-run regression coefficients. We calculate the long-run regression coefficients based on estimated coefficients from simple forecasting regressions reported at Panel (A) of Table (2.1). The standard errors are computed from the standard errors of simple forecasting regressions by using delta method. The t statistics for Δd is for the hypothesis of $\beta_d^l = -1$, while the t statistics for r is for the hypothesis of $\beta_r^l = 0$.

The left panel of Figure (2.2) plots the joint distribution of return forecasting coefficient β_r and dividend growth forecasting coefficient β_d. Under the null hypothesis that equity returns are unpredictable, it is only about 15.8% of the time that return forecasting coefficients produced by Monte Carlo simulations are larger than the sample estimates reported at Table (2.1). Therefore, we cannot reject the null at the conventional levels, leading to weaker evidence for the return predictability.

However, as discussed above, the variation in dividend yield must mechanically come from the changing expected equity returns or dividend growth, the fact that returns are not predictable must mean predictable dividend growth. It is evident from the joint distribution shown at Figure (2.2) that Monte Carlo simulations almost could not produce a dividend growth forecasting coefficient larger than the estimated value from the sample. In sum, even taking into account the small-sample bias, the overwhelming evidence against the predictable dividend growth give us very strong evidence for the predictability of equity returns.

In addition, multiplying both sides of Eq. (2.6) by $(d_t - p_t)$ and take expectations, we could yield Eq. (2.11). By dividing both sides of (2.11), we can rewrite it as Eq. (2.11). Note that the right side of Eq. (2.12) is the regression coefficients (denoted (β_r^l and β_d^l) of weighted long-run cash flow ($\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}$) and weighted long-run equity returns ($\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$) on dividend yields $(d_t - p_t)$. The long-run regression coefficients β_r^l and β_d^l represent the fraction of variance in the dividend yield attributable to changes

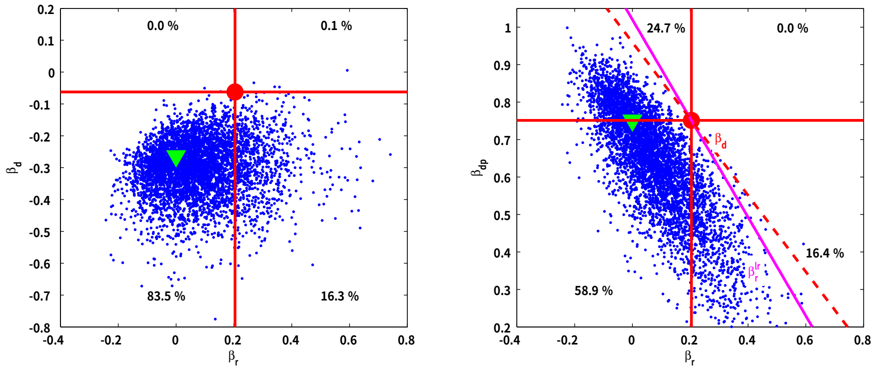


Figure 2.2: Joint Distribution of (β_r, β_d) and (β_r, β_{dp})

Note: The left-hand-side panel shows the joint distribution of (β_r, β_d) and the right-hand-side panel is the joint distribution of (β_r, β_{dp}). The reversed triangles and the circles give the the null hypothesis and sample estimates respectively. The results are based on Monte Carlo simulation with 5000 draws. Percentage numbers are the fraction of 5000 simulations that fall in the corresponding quadrants separated by the solid lines. The diagonal dashed line marked "β_d" represents the line of $\beta_r = 1 - \rho\beta_{dp} + \hat{\beta}_d$; points above and to the right of the dashed line are draws in which β_d is larger than the corresponding sample value $(\beta_d > \hat{\beta}_d)$. The diagonal solid line marked "β_r^l" shows the line of $\beta_r/(1-\rho\beta_{dp}) = \hat{\beta}_r^l$; points above and to the right of the line are draws in which β_r^l is larger than the corresponding sample value $(\beta_r^l > \hat{\beta}_r^l)$.

in expected future cash flow and changes in expected equity returns.

$$Var(dp_t) = Cov(\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}, dp_t) - Cov(\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}, dp_t), \tag{2.11}$$

$$1 = \frac{Cov(\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}, dp_t)}{Var(dp_t)} - \frac{Cov(\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}, dp_t)}{Var(dp_t)}. \tag{2.12}$$

We also have an identity linking the long-run regression coefficient β_r^l to one-horizon regression coefficient β_r as follows:[6]

$$\beta_r^l = \frac{\sum_{j=1}^{\infty} \rho^{j-1} Cov(r_{t+j}, dp_t)}{Var(dp_t)} = \sum_{j=1}^{\infty} \rho^{j-1} \beta_{dp}^l \beta_r = \frac{\beta_r}{1 - \rho\beta_{dp}} \tag{2.13}$$

We produce the long-run regression coefficient estimates based on Eq. (2.13) and the coefficient estimates from Panel (A) of Table (2.1). We also employ the delta method to calculate the standard errors for long-run regression coefficients based on the simple forecasting regression results. The results are reported at Panel (B) of Table (2.1).[7] Eq. (2.12) says that the long-run regression coefficient estimates β_r^l and β_d^l represent the fraction of variance in the dividend yield attributable to changes in expected future cash flow and changes in expected equity returns. It is evident that almost all variance in dividend yield could be accounted for by this covariance with future equity returns.

[6] We also have similar identity linking the long-run regression coefficient β_d^l to one-horizon regression coefficient β_d.

[7] The test statistics for return coefficient $\beta_r^l = 0$ should be the same as the results for dividend growth test $\beta_d^l = -1$ by the identities (2.12). Since it is only approximate identities, we could observe some small difference remaining.

Moreover, we plot the small-sample joint distribution of simple regression coefficients β_r and β_{dp} at the right-hand-side panel of Figure 2.2. We could show in (β_r, β_{dp}) space that how often long-run regression coefficients for returns β_r^l are larger than the sample value under the null $\beta_r^l = 0$. The diagonal dashed line marked "β_r^l" shows the line of $\beta_r/(1-\rho\beta_{dp}) = \hat{\beta}_r^l$. Points above and to the right of the dashed line are draws in which β_r^l is larger than the corresponding sample value ($\beta_r^l > \hat{\beta}_r^l$). The results tell us that it is very rare that Monte Carlo simulations would produce long-run return forecasting coefficient estimates larger than the corresponding estimated value from the data. Therefore, we can again reject the null that returns are not predictable.

More importantly, tests based on long-run return forecasts and dividend growth forecasts would give greater statistical power, when there are strongly negative correlation between return shocks and dividend yield shocks in the data, as pointed out by Cochrane (2008a). Table (2.1) shows clearly that return shocks and dividend yield shocks are strongly and negatively correlated with a correlation coefficient about -0.8. In contrast, the correlation between dividend growth shocks and dividend yield shocks are only half of that number. Intuitively, when there are strongly negative correlation between return shocks and dividend yield shocks, it would be also true that coefficient estimates β_r and β_{dp} are strongly and negatively correlated. In other words, you are more likely to come up with small β_r if you get a very large estimate of β_{dp} in your sample. On the other hand, we need both a large β_r and β_{dp} to get a large long-run coefficients $\beta_r^l = \frac{\beta_r}{1-\rho\beta_{dp}}$. Therefore, it would be harder to produce large long-run return forecasting coefficients under the null. The same arguments apply to the coefficient estimates of β_d, since we have the identity $\beta_d = \beta_r - (1 - \rho\beta_{dp})$ linking the one-period forecasting coefficients.[8]

Decomposition of Dividend Yield

In this section, we would first compute each term in the approximate identity (2.6) to decompose dividend yields based on the forecasting regression results from Table (2.1). The results are plot in Figure (2.3). This figure shows clearly about how much the variations in expected returns and expected dividend growth have contributed to the variation in dividend yield. It is evident that the movement of the expected returns is almost identical to that of dividend yield. In other words, the expected return term explains almost all variation in dividend yield.

Following Campbell and Shiller (1988), we also compute the variance of each component in the approximate identity (2.6) to decompose the variance of dividend yield to the variance of expected returns, the variance of expected dividend growth and covariance between them. The variance decomposition allows us to examine quantitatively how much the variation in dividend yield comes from the changes in expect returns and expected dividend growth. The results are reported at Panel (A) of Table (2.2).

It is clear that the contribution of expected equity returns as a percentage

[8] Please see Cochrane (2008a) for more detailed arguments.

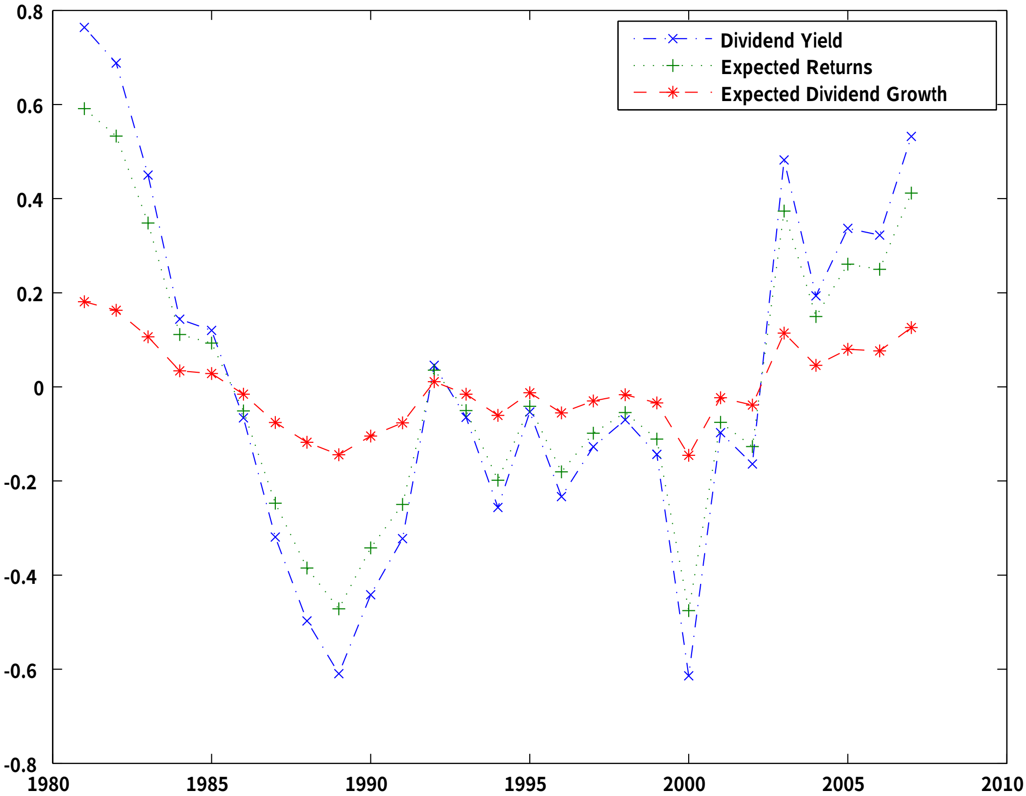


Figure 2.3: Decomposition of Dividend Yield

of the variance of dividend yield is far more important than that of expected dividend growth. Since dividend yield is not constant, it must forecasts changes in expected equity returns or expected dividend growth. Our results favor strongly that equity returns are predictable. It is also worth noting that the fraction of variance of expected returns and expected dividend growth do not sum up to one. It reminds us that the two components are correlated; this is not an orthogonal decomposition.

Decomposition of Equity Returns

In addition to exploit implications for the predictability of equity returns from the variation in dividend yield, our present-value framework could also help examine the relative importance of economic forces driving the equity returns by using the forecasting results based on dividend yield. In particular, we decompose equity returns based on Eq. (2.7) and the regression results from Table (2.1). The results are plotted in Figure (2.4). It is clear that the unexpected equity returns are closely related with the movement of changes in expectation in future expected returns rather than future dividend growth.

Following Campbell (1991) and Campbell and Ammer (1993), we also compute the variance of each term in Eq. (2.7) to show exactly how these terms combined to explain the variation in equity returns. Note that when examining the effect of expected dividend growth on the variation in equity returns, we need to exclude the mechanical effect of current dividends. The variance decomposition results are reported at Panel (B) of Table (2.2). It is

Table 2.2: Variance Decomposition based on Dividend Yield

Panel A: Variance Decomposition of Dividend Yield

	Dividend growth	Equity returns
Variance	0.008	0.085
Share	(0.056)	(0.600)

Panel B: Variance Decomposition of Equity Returns

	Expected Returns	Current Dividends	Future Dividends	Future Returns
Variance	0.006	0.019	0.003	0.033
Share	(0.124)	(0.395)	(0.064)	(0.687)

Note: Panel (A) of this table reports variance decomposition of dividend yield to the variance of expected returns, the variance of expected dividend growth and covariance between them. The covariance term is not reported here. Panel (B) reports variance decomposition of equity returns into four terms: changes in expected returns, changes in expectation in future expected returns, changes in expectation in expected current dividend growth, and changes in expectation in expected future equity payout growth.

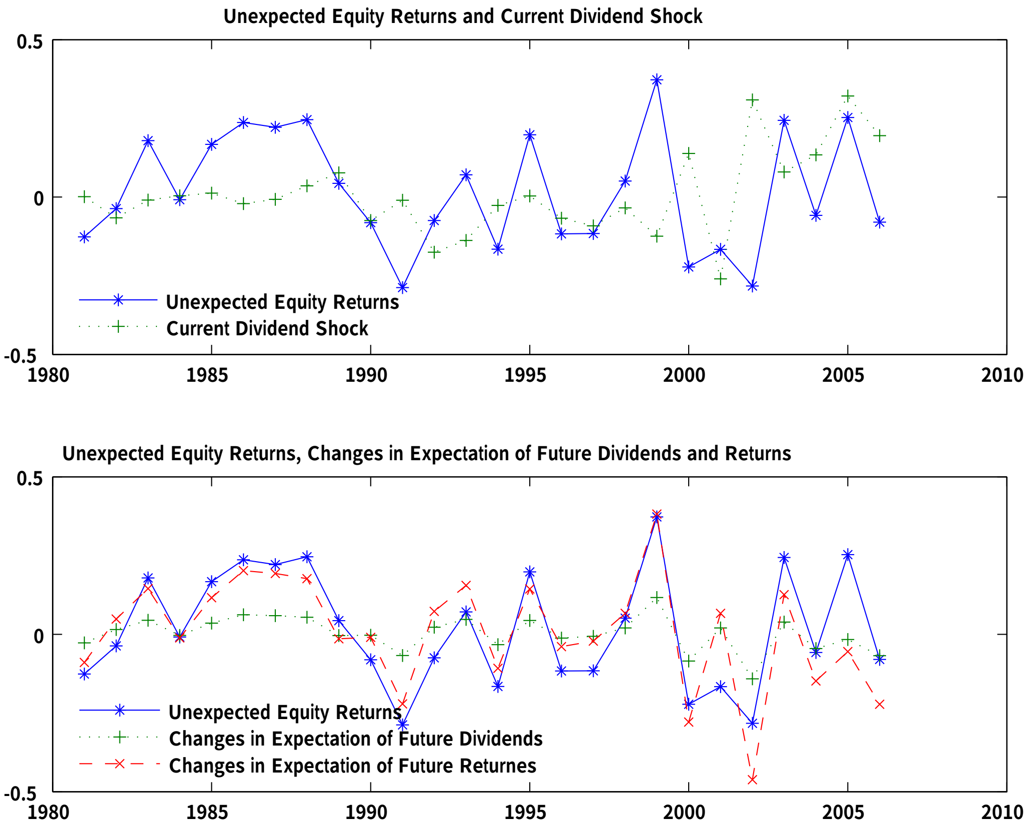


Figure 2.4: Decomposition of Equity Returns based on Dividend Yield

evident that current dividends do matters for the variation of equity returns, while the effect of expected future dividend growth is negligible. Of course, it is the changes in expectation in future equity returns that dominate the variation in equity returns.

Impulse Response Function: Constrained VAR vs. Unconstrained VAR

Since dividend yield tends to be highly persistent, some economists (e.g. Boudoukh et al. 2007) have questioned its stationarity. In this section, we employ the impulse response function to examine the stationarity of dividend yield. In particular, we look at the question about whether the impulse response function of dividend yield eventually decays to its mean. If dividend yield is stationary, it would revert back to original place after any shock in the forecasting system. We plot the response of dividend yield to an expected return shock and a dividend growth shock at the top panels of Figure (2.5) (labeled unconstrained VAR).[9] We identify an expected return shock as a return shock without contemporaneous movement in dividends. The result shows that the impulse response of dividend yield to either shock is entirely stationary.

In addition to the impulse response function of dividend yield, we plot the

[9]We report the impulse response function based on the forecasting results by adding a lagged dividend yield and returns as the forecasting variables to Eq. (2.10). However, the results based on Eq. (2.10) alone would be more like the constrained case.

responses of dividends, prices, and equity returns to an expected return shock and a dividend growth shock as well. We also plot the response function of those variables by restricting the null hypothesis that returns are predictable but dividend growth is not predictable at the bottom panels of (2.5) (labeled constrained VAR), and compare them to the unconstrained case. It is clear from Figure (2.5) that both cases display very similar pattern of impulse responses, implying that the null hypothesis with predictable equity returns and unpredictable dividend growth seems to be a good approximation to the real world.

On the one hand, a positive dividend shock raises prices and returns immediately and proportionally. As a result, dividend yield would not change. Since the changes in dividends lead to permanent changes in prices, it does not forecast future equity returns. On the other hand, a positive shock in expected returns isolated from dividend news leads to a decline in ex-post equity returns. Since this shock leads to transitory decline in prices, it does signal high subsequent equity returns.

2.5.2 Empirical Results based on Equity Payout Yield

Dividends may be an appropriate measure of cash flow for an investor who owns one share of a firm's equity claim. If you take a macro view to think of a representative investor who owns all outstanding shares of the firms together, a more appropriate measure of cash flow may be equity payout incorporating equity repurchase and equity issuance. In this section, we

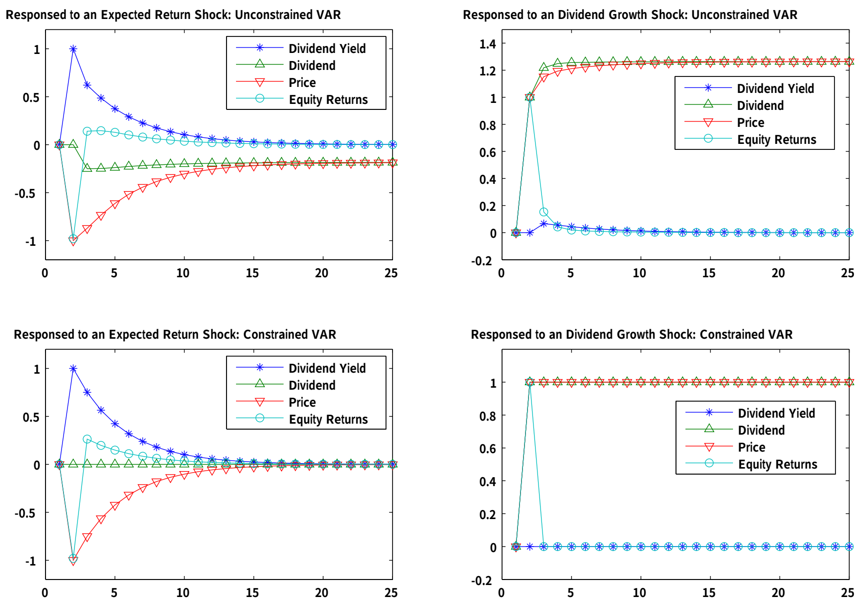


Figure 2.5: Impulse Response Function: Constrained VAR vs. Unconstrained VAR

explore the implications for equity returns based on equity payout yield.

Forecasting Regressions

We employ the forecasting regressions in Eq. (2.14) of log equity returns, log equity payout growth, and log equity payout yields in annual frequency from 1980 to 2008, with log equity payout yields as the only right-hand side forecasting variable to focus on the forecasts based on equity payout yield. The estimation results are reported at Table (2.3).

$$\begin{aligned}
r_{t+1} &= \beta_r \cdot ev_t + \eta_t^r, \\
\Delta e_{t+1} &= \beta_d \cdot ev_t + \eta_t^e, \\
ev_{t+1} &= \beta_{ep} \cdot ev_t + \eta_t^{ev}.
\end{aligned} \tag{2.14}$$

The first row shows that equity payout yield is not a good predictor of equity returns. the forecasting coefficient is not only statistically insignificant, but also wrong in the economic sense. The second row, however, tells us that equity payout yield has predictive power about future equity payout growth. Finally, the third row shows that equity payout yield is less persistent than dividend yield.

In order to shed light on the role of other cash flow such as equity repurchase and issuance other than dividends, we decompose the equity payout yield into equity payout-dividend ratio and dividend yield to estimate forecasting regressions of log equity returns, log equity payout growth, and log

Table 2.3: Forecasting Regressions based on Equity Payout Yield

	Estimates			Error Terms		
	Coefficients	SE	t Value	r	Δe	ev
r	-0.071	0.289	-0.247	0.218	0.879	-0.331
Δe	-0.410	0.111	-3.700	0.879	0.208	0.159
ev	0.675	0.170	3.968	-0.331	0.159	0.107

Note: This table reports the estimation results of forecasting regressions in Equations (2.14) of log equity returns, log equity payout growth, and log equity payout yields in annual frequency. The sample period is from 1980 to 2008. We report GMM-corrected heteroskedasticity-consistent standard errors. The diagonal of the error terms matrix are standard deviations of the regression errors, while the off-diagonal are correlation between errors.

equity payout-dividend ratio, and log dividend yields.[10] This would help us to understand why equity payout yield is not a good return predictor as dividend yield. The estimation results are reported at Table (2.4).

The left hand of Table (2.4) is forecasting coefficients of log equity returns and log equity payout growth on log dividend yield, while the right hand is forecasting coefficients of log equity returns and log equity payout growth on log equity payout-dividend ratio. On the one hand, the forecasting coefficient of equity payout-dividend ratio on equity returns is significant economically and statistically. It says that when other cash flow other than dividends is

[10]Equity payout yield is the sum of equity payout-dividend ratio and dividend yield. The terminology of equity payout-dividend ratio follows Larrain and Yogo (2008).

low, large amount of equity issuance to raise funds from the equity market for instance, it may signal high subsequent equity returns. Although both dividend yield and equity payout-dividend ratio have significant predictive power on equity returns, equity payout yield, which is the sum of dividend yield and the equity payout-dividend ratio, cannot forecast equity returns. It may be attributed to the fact that dividend yield and equity payout-dividend ratio differ in the direction in forecasting returns. As a result, their predictive power on equity returns may be canceled out, when they add up together.

Table 2.4: Decomposing the Equity Payout Yield

	Dividend yield			Equity payout-dividend ratio		
	Coefficients	SE	t Value	Coefficients	SE	t Value
r	0.209	0.096	2.171	-0.116	0.039	-2.979
Δe	0.150	0.121	1.242	-0.139	0.043	-3.191

Note: This table reports the forecasting results of log equity returns and log equity payout growth on log dividend yield (Left) and log equity payout-dividend ratio (Right) respectively. The sample period is from 1980 to 2008. The standard errors include a GMM correction for heteroskedasticity.

We can also observe that equity payout-dividend ratio has significantly predictive power on equity payout growth. Higher current equity payout-dividend ratio signals lower subsequent equity payout. We may ask a question about what the economic reasons is for the predictability of equity payout growth. Why is dividend growth not forecastable, while there are predictable components in equity payout growth. One potential explanation is that dividend and equity payout may consist of cash flow with different characteristics. As Hall (2001b) and Hall (2001a) have argued that dividend represents mainly permanent components of cash flow generated from corporations. In contrast, equity payout may be also greatly influenced by transitory variation in cash flow other than permanent changes reflected in dividends. As a result, dividend may be close to random walk to present no predictability, while equity payout are much more variable with transitory components that is predictable.

Decomposition of Equity Payout Yield

We compute each term in the approximate identity (2.8) to decompose equity payout yield based on the forecasting regression results from Table (2.3). The results are plot in Figure (2.3). We also compute the variance of each component in the approximate identity (2.8) to decompose the variance of equity payout yield to the variance of expected returns, the variance of expected equity payout growth and covariance between them. The variance decomposition allows us to examine quantitatively how much the variation in equity payout yield comes from the changes in expect returns and expected equity payout growth. The results are reported at Panel (A) of Table (2.5). It is clear that the variation in equity payout yield is dominated by changes in expected equity payout growth.

Since agent's expectation about expected future returns is not observable, we can only infer it from forecasts based on predicting variables. Valuation

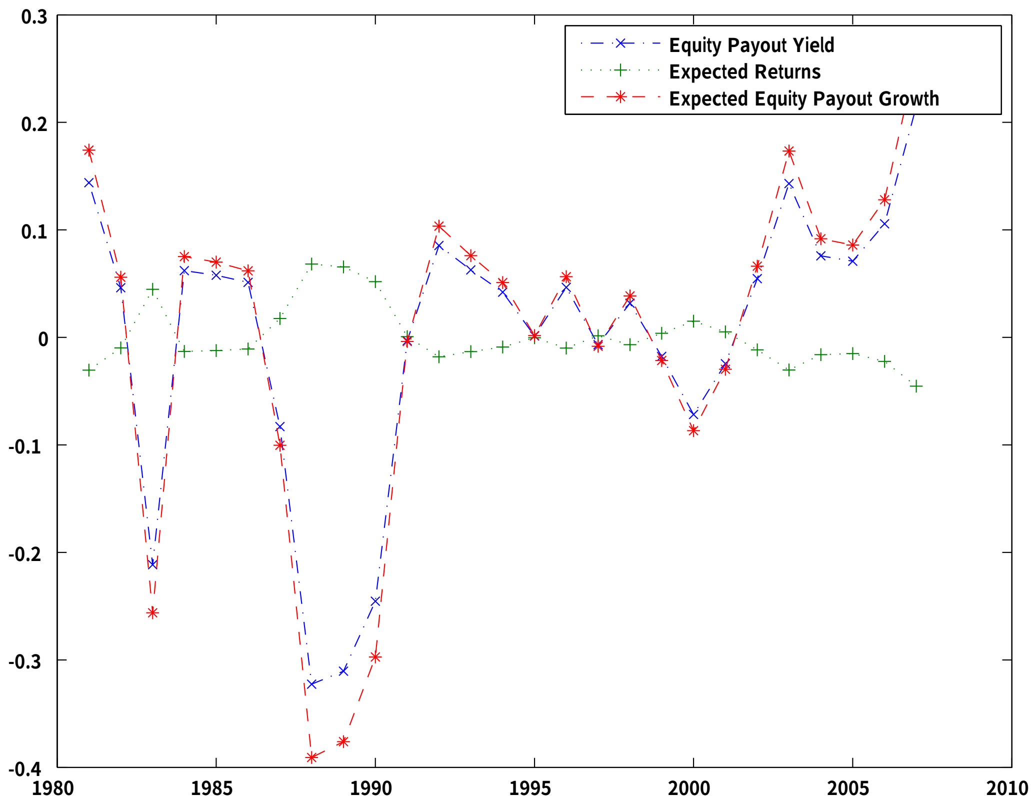


Figure 2.6: Decomposition of Equity Payout Yield

Table 2.5: Variance Decomposition based on Equity Payout Yield

Panel A: Variance Decomposition of Equity Payout Yield

	Equity payout growth	Equity returns
Variance	0.026	0.001
Share	(1.467)	(0.045)

Panel B: Variance Decomposition of Equity Returns

	Expected Returns	Current Payout	Future Payout	Future Returns
Variance	0.002	0.043	0.016	0.004
Share	(0.044)	(0.912)	(0.342)	(0.102)

Note: Panel (A) of this table reports variance decomposition of equity payout yield to the variance of expected returns, the variance of expected equity payout growth and covariance between them. The covariance term is not reported here. Panel (B) reports variance decomposition of equity returns into four terms: changes in expected returns, changes in expectation in expected future returns, changes in expectation in expected current equity payout growth, and changes in expectation in expected future equity payout growth.

ratios such as dividend yield and equity payout yield are central to forecasting because they reveal a slice of agent's expectation about expected future returns and expected future cash flow. Although the equity payout yield implies much weaker evidence for return variation, it does not necessarily mean that return is not predictable. The two models based on dividend yield and equity payout yield use different sets of conditioning information, it is therefore not surprising to see different implications for the return predictability and the driving forces of return variation.

The approximate identity (2.8) says that the variation in equity payout yield must mechanically comes from the changing expected equity returns or cash flow or both. However, this slice of expectation about expected future returns and expected future cash flow apply only to forecasts based on equity payout yield. This result simply means that equity payout yield is not good forecasting variable for equity returns. Other variable such as dividend yield, consumption-wealth ratio may still help forecast equity returns. Therefore, we can conclude returns are not predictable, only if we infer small variation in returns from all potential forecasting variables.

Decomposition of Equity Returns

Similar to the forecasts based on dividend yield, based on Eq. (2.9) and the regression results from Table (2.3), we decompose equity returns into four terms: changes in expected returns, changes in expectation in expected future returns, changes in expectation in expected current equity payout growth, and changes in expectation in expected future equity payout growth. Note that we separate the mechanical effect of current equity payout growth from the effect of future equity payout growth. This decomposition help us to examine the relative importance of economic forces driving the equity returns based on equity payout yield forecasts. The results are plotted in Figure (2.4). It is evident that the term of unexpected equity returns is mostly associated the movement of changes in expected current equity payout.

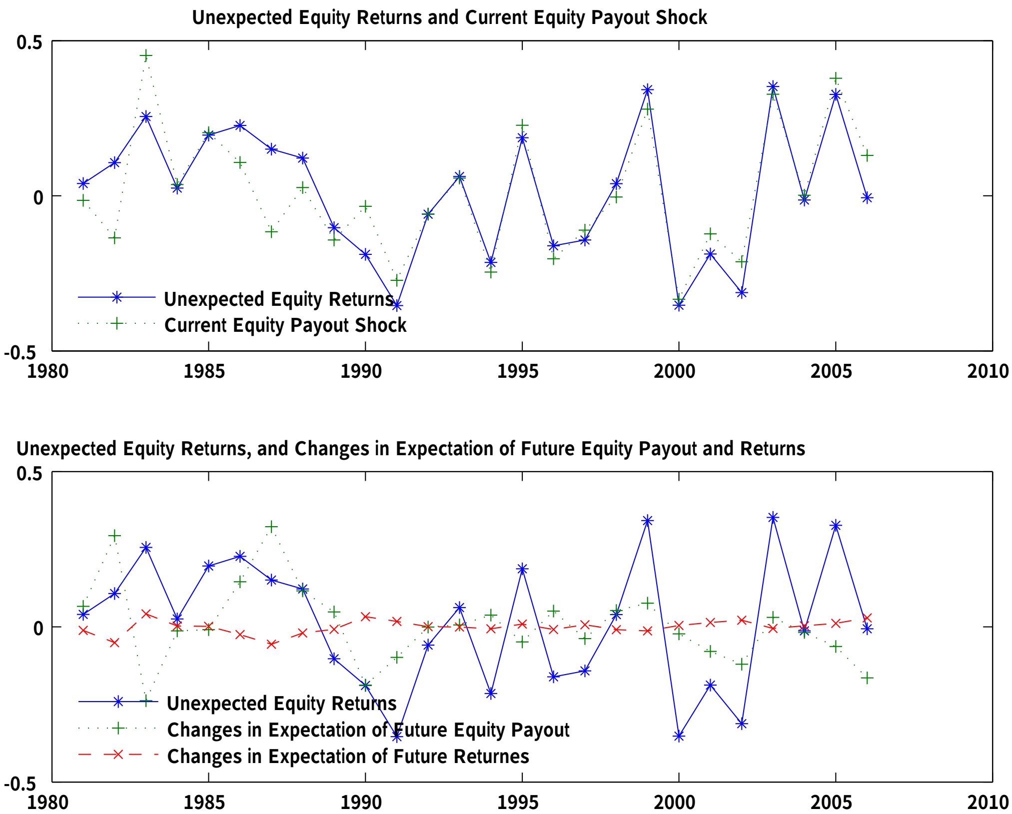


Figure 2.7: Decomposition of Equity Returns based on Equity Payout Yield

We also calculate the variance of each term in Eq. (2.9) to show quantitatively how important these terms are in the determination of the variation in equity returns. The variance decomposition results are reported at Panel (B) of Table (2.5). This table shows that the variation in equity returns is dominated by changes in expectation in current equity payout growth, while the effect of future equity payout growth is much less significant than current equity payout growth. Combining this fact with the variance decomposition of equity returns based on dividend yield forecasts reported at the previous section, we may be quite confident to conclude that changes in expected future cash flow play only a small role in the variation of equity returns.

2.6 Conclusion

This paper explores the implications of a dynamic accounting identity for the dynamics of equity returns by using data about cash flow and market equity value of Japanese private non-financial corporations. In particular, we study the role of fluctuations in dividend yield and equity payout yield for predicting equity returns. Our results provide significant evidence for the predictability of equity returns of Japanese corporations, and show that dividend yield is a better predictor of equity returns than equity payout yield. Moreover, we show that while the dividends are not predictable either by dividend yield or equity payout yield, there are predictable components in equity payout. The predictable components could largely be attributed to other cash flow such as equity repurchase and issuance rather than dividends.

In addition to implications about the variation in expected equity returns, we decompose equity returns into changes in current cash flow, changes in expected future cash flow and changes in expected equity returns, and compute the variance of each component to show how much variation in equity returns are due to changes in expected equity returns and expected changes in cash flow. Our variance decomposition result based on dividend yield shows that the variation in equity returns is dominated by changes in expected future equity returns, while the results based on equity payout yield shows that the variation in equity returns is mainly explained by changes in current cash flow. Contrary to previous studies, we find that changes in expected future cash flow play a very small part in the variation of equity returns. This conclusion is robust whether we measure the cash flow by dividends or equity payouts.

Our results have important implications for our understanding about the dynamics of the overall equity market. Of course, empirical results based on historical data may not hold true for the future. This time could be totally different from what happened in history. However, if we apply the results to the current fluctuations in the equity market, we can have a pretty optimistic view about the future of Japanese economy. A plausible story seems to be as follows. Initially, bad news about the earnings and the dramatic rise in credit spreads may contributed to the decline of the equity market. Since then, several factors such as the rising uncertainty about the equity market and overall macro economy possibly due to the ambiguity of the policy response and opaque disclosure about the loss of financial institutions, the increase of risk aversion of market participants, and the declining ability of many market participants especially highly leveraged investors and institutions to take equity market risk, may dominate fluctuations of the equity market. These factors do not only amplify an initial decline of equity market into a historical plunge, but also contribute to the large swings observed in the market. However, the dramatic decline of equity market does not necessarily reflect a pessimistic outlook about the future earnings of Japanese corporations. Rather, history tells us that the dramatic changes in the equity market over the last two years may have little to do with investor's gloomy prospect about future cash flow of Japanese corporations.

Chapter 3

Exploring the Driving Force and Price Adjustment of the J-REIT Market

3.1 Introduction

In this section, we turn attentions to the value of claims to a particular object – real estate. First, real estate market is a critical components of asset market. Some even consider it as the the largest financial asset in the world. After all, transactions of real estate are, like all the other financial assets, conducted by exchanging of certificate documents. There is little difference between the real estate and other financial assets. As the financing technique of securitization develops, the technique of securitization get applied to once less liquid real estate to create the real estate backed security. Among them, REIT (Real Estate Investment Trust) provides a convenient way for investment in real estate, similar to the structure that mutual funds provide for investment in stocks, or money market funds provide for investment in money markets. REIT could be listed on stock exchange like shares of other corporations. It is thus natural for us to ask about whether we can acquire additional insights by exploring the implications for dynamics of returns of REIT and the underlying forces driving its variation.

Since the burst of the real estate "bubble" in 1990, real estate prices in Japan have been declining all the way through 2004, with some signs of price stabilization and increases in recent two years. Japan has adopted the Real Estate Investment Trust (usually called J-REIT) scheme in 2001, as a way to facilitate investments and transactions in the real estate market. There has been little research about J-REIT, most of which is devoted to the performance analysis.[1].

We are looking at the question of what forces have driven the movement of the J-REIT market by employing the log-linearization and VAR method proposed by Campbell and Ammer (1993) to decompose the excess J-REIT equity return into three components: future dividends, real interest rates, and excess returns. In other words, we would like to identify which type of

[1] A large amount of researches about REIT have been on the relationship across REIT markets, between REIT and unsecuritized real estate assets, or, between REIT and stock and bond markets (e.g. Payne and Mohammadi, 2004; Glascock, 2000; Seck, D, 1996).

news (future dividends, real interest rates, or excess returns) has played the most significant part in the movement of the J-REIT return. Moreover, we also take the question further to examine whether or not the J-REIT market has fully incorporated those news immediately, to do so, we will adapt the methodology developed by Fu and Ng (2001). The results indicate that the news about future dividends combined with future excess returns account for most of the movement of the J-REIT return, while the effect of real interest rates are almost negligible. The results also show that the J-REIT market has assimilated market news fully within a month lag. The much quicker price adjustment of the J-REIT market seems to suggest that it helped improve the informational efficiency of the real estate market in Japan. On the other hand, it also suggests that Japan may need to promote the securitization of real estate assets further on the basis of efficient asset pricing.

3.2 Methodology

3.2.1 The Decomposition of Excess J-REIT Returns

We decompose the excess J-REIT return into unobservable components by using the log-linearization developed by Campbell and Shiller (1988) and Campbell (1991), in which the news is decomposed as:

$$e^{y}_{t+1} = \tilde{e}^{d}_{t+1} - \tilde{e}^{r}_{t+1} - \tilde{e}^{y}_{t+1}, \tag{3.1}$$

$$\tilde{e}^d_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}, \tag{3.2}$$

$$\tilde{e}^r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j},$$

$$\tilde{e}^y_{t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j y_{t+1+j},$$

where y_{t+1}, d_{t+1}, and r_{t+1} denoted the log excess return on the J-REIT equity, the log dividends, and the log return in the money market (the risk-free interest rate) during period t to $t+1$, respectively. The variable e_{t+1} denotes the unexpected part, news, or revisions in expectations during period t to $t+1$: $x_{t+1} - E_t x_{t+1}$. The tilde means a discounted sum defined above, and ρ is the discount factor. Following Campbell and Ammer (1993), we set it as 0.9962.

3.2.2 Empirical Proxies

Since the revisions in expectations are unobservable, we need to construct empirical proxies for the expectations in the above equation (3.1) to implement the decomposition of excess J-REIT return. We adopt the vector autoregressive (VAR) methodology proposed by Campbell and Ammer (1993) to create proxies for the relevant expectation. In particular, we construct the forecast of variables by VAR; the revisions in these forecasts are then used as proxies for revisions in investor's expectations. We should include at least the variables (two in our case, the excess J-REIT return and the real interest rate) we want to forecast, and other variables useful in forecasting the variables of interest. We roughly follow Campbell and Ammer to include the dividend-price ratio and the relative bill rate[2] into our VAR. In addition, we also include the excess return of the overall stock market:

$$\begin{aligned} z_{t+1} &= Az_t + \epsilon_{t+1}, \qquad (3.3) \\ e^y_{t+1} &= s_y \epsilon_{t+1}, \end{aligned}$$

where z is the 5×1 vector containing our endogenous variables of the VAR system, A is the coefficient matrix of the VAR, and ϵ is the error vector.

The unexpected excess return can be easily obtained from the error term of the VAR system by selecting an appropriate selection matrix. Given that the excess return is the first element of the VAR system, the selection matrix for innovations to the excess return in the case of first-order VAR[3] is just the first column of a 5×5 identity matrix, denoted s_y. Similarly, s_r denotes the selection matrix for innovations to the real interest rate. We could also obtain the proxies for revisions in long-horizon expectations of other variables of interest readily by using equations below:[4]

$$\begin{aligned} e^y_{t+1} &= s_y \epsilon_{t+1}, \qquad (3.4) \\ \tilde{e}^y_{t+1} &= s_y \rho A (I - \rho A)^{-1} \epsilon_{t+1}, \\ \tilde{e}^r_{t+1} &= s_r (I - \rho A)^{-1} \epsilon_{t+1}, \\ \tilde{e}^d_{t+1} &= \tilde{e}^r_{t+1} + \tilde{e}^y_{t+1} + e^y_{t+1}. \end{aligned}$$

[2]It is defined as the risk-free rate minus its 12-month lagged moving average to capture the dynamics of the risk-free rate.

[3]Any VAR(p) ($p > 1$) process could be represented in the form of first-order VAR.

[4]We are using the fact that: $(E_{t+1} - E_t) z_{t+1+j} = A^j \epsilon_{t+1}$.

3.2.3 Variance Decomposition for the Excess J-REIT Returns

Having obtained the proxies for revisions in expectation, we could use the dynamic accounting identity defined in equation (3.1) to decompose the variance of the excess J-REIT return into the sum of variance and covariance terms as follows by taking into account the possible correlation among various components. The relative contribution of different components to the movement of the current excess J-REIT return could then be measured by the variance of that component, calculated as the percentage share of the variance of the current excess J-REIT return:

$$\begin{aligned} Var(e^y_{t+1}) =& Var(\tilde{e}^d_{t+1}) + Var(\tilde{e}^r_{t+1}) + Var(\tilde{e}^y_{t+1}) \\ & - 2Cov(\tilde{e}^d_{t+1}, \tilde{e}^r_{t+1}) - 2Cov(\tilde{e}^d_{t+1}, \tilde{e}^y_{t+1}) \\ & + 2Cov(\tilde{e}^r_{t+1}, \tilde{e}^y_{t+1}). \end{aligned} \tag{3.5}$$

It is worth noting that the Campbell-Ammer (1993) approach treats the dividends component as a residual of the estimation, which means we tend to overstate the return volatility of dividends if the VAR understates the predictability of excess returns.

3.2.4 Speed of Price Adjustment in the J-REIT Market

Fu and Ng (2001) developed a way to identify the speed of an asset's price adjustment to news within the framework of Campbell and Shiller. Their logic goes as follows. If the market is efficient, in the sense that the future innovations in excess returns are independent innovations, they should be negatively correlated with the current innovation. However, suppose it takes another two periods for full price adjustment to the current news (say the news about dividends $\tilde{e}^d$), we would have $\tilde{e}^d = e^y(0) + \rho e^y(1) + \rho^2 e^y(2)$, where $e^y(j) = (E_{t+1} - E_t)y_{t+1+j}$ for $j = 0, 1, 2$. If the existence of future innovations $e^y(1)$ and $e^y(2)$ is only to complete the current price adjustment due to the market friction, they must become positively related to the current innovation. Fu and Ng (2001) proposed that we could view positive correlations between current innovations and innovations in subsequent expected excess returns as the evidence of price adjustment frictions, indicating that the current adjustment fails to assimilate the market news fully.

3.3 Data

We use the dividends and splits adjusted Quick Reit Index's price change minus the 1-month general collateral repurchase rate (usually called GC Repo rate)[5] to measure the excess return of J-REIT equity (denoted e), and the 1-month GC Repo rate minus the log difference in the non-seasonally adjusted Consumer Price Index (CPI) to represent the real interest rate (denoted r). We should include at least the above two variables, and any other variable that is judged to be useful in forecasting variables of interest. Roughly following Campbell and Ammer (1993), we also include the the dividend-price ratio, the relative bill rate, and the excess return of the overall stock market into our VAR. The dividend-price ratio of the Quick Reit Index (denoted dp) is calculated as total dividends (dividends per share times the total outstanding shares) paid over the previous financial closing divided by the current market capitalization (current stock price times the total outstanding shares). The 3-month GC Repo rate minus its 12-month lagged moving average is used as a measure of the relative bill rate (denoted rb). Finally, the Nikkei 225's dividends and splits adjusted price change minus the 1-month GC Repo rate is used as a measure of the excess return of the overall stock market (denoted en). The monthly Quick Reit Index is obtained from Bloomberg; the monthly GC Repo rate is obtained from the website of the Bank of Japan; the monthly CPI is obtained from the website of the Japan Statistics Bureau; all the other data are obtained from the NEEDS-FinancialQUEST database. The sample period for all these monthly series is from Dec 2001 through May 2007.

[5] "GC Repo rate" is the typical rate in the money market, and commonly regarded as representing the risk-free rate in Japan.

3.4 Results

Table 3.1 reports coefficient estimates for the monthly five-variable first-order VAR. We chose the number of lags through Akaike Information Criterion. It is evident that the joint significances of the explanatory variables in the VAR forecasting are statistically significant for all other than the excess return of Nikkei 225 index. We also find that the dividend-price ratio enter positively and can effectively forecast the excess return of J-REIT equity. The real interest rate process seems to be a simple AR(1) with a coefficient of about 0.4, showing some persistence. The dividend-price ratio is mainly forecast by its own lag, with a coefficient above 0.8, as well as the lagged excess J-REIT return, with a small negative coefficient. The relative bill rate seems to follow a highly persistent AR(1) process with a coefficient of more than 0.9. The results here are quite consistent with the pattern reported by Campbell and Ammer (1993), and Fu and Ng (2001).

Table 3.2 reports the variance-covariance decomposition of the current excess J-REIT return into the variance of news in expectations of future excess returns, real interest rates, dividends, and the covariances between them. The column "Total" reports the total contribution, while the column "Share" shows the contribution as a percentage of the variance of excess J-REIT returns. It is evident from the table that the news about dividends played the most significant role in the movement of the J-REIT return, and the future excess returns followed. Our results about J-REIT are a little different from the earlier work on the decomposition of stock market (e.g.

Table 3.1: VAR Coefficients Estimation

	e_t	r_t	dp_t	rb_t	en_t	R^2	Sig
e_{t+1}	0.0281	0.4761	0.2124	6.1104	0.0327	0.285	0.002
	(0.133)	(0.955)	(0.066)	(4.133)	(0.091)		
r_{t+1}	0.0124	0.3756	-0.0492	0.3151	0.0027	0.205	0.030
	(0.011)	(0.111)	(0.094)	(0.409)	(0.008)		
dp_{t+1}	-0.0184	0.0025	0.8263	0.4033	-0.0003	0.994	0.000
	(0.009)	(0.083)	(0.060)	(0.236)	(0.005)		
rb_{t+1}	-0.0000	-0.0079	0.0076	0.9393	-0.0008	0.918	0.000
	(0.002)	(0.012)	(0.003)	(0.051)	(0.001)		
en_{t+1}	0.1027	2.2098	1.5013	-2.3134	0.1448	0.093	0.431
	(0.165)	(1.472)	(1.072)	(4.231)	(0.117)		

Note: This table reports coefficient estimates for a monthly five-variable first-order VAR, which includes the excess return of J-REIT equity, the real interest rate, the dividend-price ratio of J-REIT equity, the relative bill rate, and the excess return of Nikkei 225 index. The excess returns are measured in percentage points per month, while the remaining variables are measured in percentage points at annual rate. The sample period for all these series is from Dec 2001 through May 2007. The number of lags was chosen through Akaike Information Criterion. Numbers below the coefficient estimates (in round parentheses) are heteroskedasticity-consistent standard errors. R^2 is the R^2 in the regression of each endogenous variable on the VAR explanatory variables, while "Sig" denotes the joint significance of the explanatory variables in the regression.

Campbell and Ammer 1993, Bernanke and Kuttner 2005), which reports that future excess returns account for the greatest part of stock movement, while the news about the dividends play only a moderate role. It may attributed to the different characteristics of underlying assets between REIT and common stocks.

The dividends of J-REIT deserve some further comments here. J-REITs are required to distribute 90 percent of their income, while in return they are exempt from corporate income taxation. Therefore, the news about the dividends could be viewed as almost equivalent to the news about the rental income of the underlying properties in the case of J-REIT. It is thus the news about the rental income of the underlying properties that drives the J-REIT market most.

We also find that the effect of real interest rates is almost negligible, which is consistent with the earlier work on the decomposition of stock market. However, we may need some cautions about the role of real interest rates in the J-REIT market, since the nominal interest rate in Japan has been very steady at the level of nearly zero percent in the past few years, due to easing monetary policy of the Bank of Japan.

We report the R^2 statistics from simple regressions of the unexpected excess return on each estimated component as an alternative measure of the importance of that component at panel B at the bottom. The results are consistent with the above variance decomposition.

Table 3.3 reports correlation statistics between the current innovation and

Table 3.2: A Variance Decomposition of Excess J-REIT Returns

Panel A:		
	Total	Share(%)
Var(Excess return)	11.28	100.00
Var(Future return)	17.80	157.77
Var(Real rate)	0.29	2.58
Var(Dividend)	24.41	216.41
-2Cov(Dividend, Real rate)	-2.90	-25.74
-2Cov(Dividend, Future return)	-30.77	-272.72
2Cov(Future return, Real rate)	2.45	21.70

Panel B:	
	R^2
R^2(Future return)	0.0660
R^2(Real rate)	0.0012
R^2(Dividend)	0.2086

Note: This table reports the variance-covariance decomposition of the current excess J-REIT return into the variance of news in expectations of future excess returns, real interest rates, dividends, and the covariances between them. A five-variable first-order monthly VAR is employed to construct the forecast of future real interest rates and excess returns, and then calculate the proxies for the unobservable components of the unexpected J-REIT return. The column "Total" reports the total contribution, while the column "Share" shows the contribution as a percentage of the variance of excess J-REIT returns. The panel B at the bottom reports the R^2 statistics from simple regressions of the unexpected excess return on each estimated component as an alternative measure of the importance of that component.

innovations in subsequent expected returns up to six month horizons (denoted j). As stated earlier, the presence of positive correlations between current innovations and innovations in subsequent expected excess returns may suggest the existence of price adjustment frictions, while the number of periods over which the positive correlation lasts could provide a measure about the speed of price adjustment. We could observe from the table that correlation statistics are negative for all values of j but one. Our results indicate that the J-REIT market has assimilated market news fully within a month lag. In contrast, Fu and Ng (2001) reported strong evidence against the real estate market efficiency that real estate prices need about three quarters to complete the price adjustment. The much quicker price adjustment of the REIT market seems to suggest that it helped improve the informational efficiency of the real estate market in Japan. On the other hand, it also suggests that Japan may need to promote the securitization of real estate assets further on the basis of efficient asset pricing.

3.5 Conclusion

This chapter employed the log-linearization and VAR method proposed by Campbell and Ammer (1993) to decompose the excess J-REIT return into three components: future dividends, real interest rates, and excess returns, to identify which news has played the most significant part in the movement of the J-REIT return. The results indicate that the news about dividends

Table 3.3: Price Adjustment Speed

Horizon (j)	1	2	3	4	5	6
Corr($e^y(0), e^y(j)$)	0.209	-0.102	-0.210	-0.248	-0.265	-0.275
T statistics	(1.692)	(-0.813)	(-1.701)	(-2.033)	(-2.185)	(-2.268)
P value	(0.096)	(0.429)	(0.094)	(0.046)	(0.033)	(0.027)

Note: This table reports correlations between the current innovation and innovations in subsequent expected excess returns. The presence of positive correlations could be viewed as the evidence of price adjustment frictions, while the number of periods over which the positive correlation lasts could provide a measure about the speed of price adjustment. T statistics and their P values under the null of zero correlation are also reported below the correlation coefficients.

combined with future excess returns account for most of the movement of the J-REIT return, while the effect of real interest rates is almost negligible. We also take the question further to examine whether or not the J-REIT market has fully incorporated those news immediately by adapting the methodology developed by Fu and Ng (2001). Our results show that the J-REIT market has assimilated market news fully within a month lag. The much quicker price adjustment of the J-REIT market seems to suggest that it helped improve the informational efficiency of the real estate market in Japan. On the other hand, it also suggests that Japan may need to promote the securitization of real estate assets further on the basis of efficient asset pricing.

Chapter 4

Capital Ratios and the Cross-Section of Bank Stock Returns

4.1 Introduction

The Basel Accord negotiated in 1988 among the G10 countries, attempted to unify the capital constraints across countries, required banks to maintain their risk-based capital ratios no less than 8%. Since then, the BIS capital ratio has long been used as a significant tool of bank regulators to assess the safety of banks. Banks with higher BIS capital ratios have been regarded safer than those with lower BIS capital ratios, because they have more buffer capital to shocks. However, the BIS standard entails essentially a book-valued capital level. The recent financial crisis reminds us that book-valued capitals may not be functioning like a cushion that prevents banks from insolvency as we expected before,[1] when the value of its assets falls. Moreover, it seems that neither market participants nor regulators are watching BIS ratios to assess the safety of banks, especially in the financial turmoil. Even the BIS standard is well designed to begin with; it could soon become obsolete as rapid innovations in banking industry may provide means of regulatory arbitrage to undermine the effectiveness of the regulation. Therefore, the BIS capital ratio may not be an appropriate indicator of measuring the riskiness of banks.[2]

Market[3], however, may provide informative and comprehensive indicators to help assess the riskiness of a bank more accurately and timely. Market-based indicators are generally forward looking, and could incorporate the relevant information, both in the form of formal knowledge and informal knowledge, from a wide range of sources very quickly.[4] Moreover, they reflect the overall assessment from the market instead of a bank's assessment of itself

[1]Although most previous empirical researches and bank regulators have focused on book values, some (e.g. Marcus 1983) still have long been argued that market values provide better estimates of the protection afforded by capital. Capital structure literatures (e.g. Welch 2004) have also used market values of capital to measure the ownership of the firm by equity holders.

[2]See also Santos (2000) for a comprehensive survey showing that BIS capital requirement is not only theoretically ambiguous, but also may not help assess the safety of banks practically.

[3]See Flannery (1998) for a survey of market-based information about bank risks.

[4]See Hayek (1945) for arguments of the use of knowledge in society.

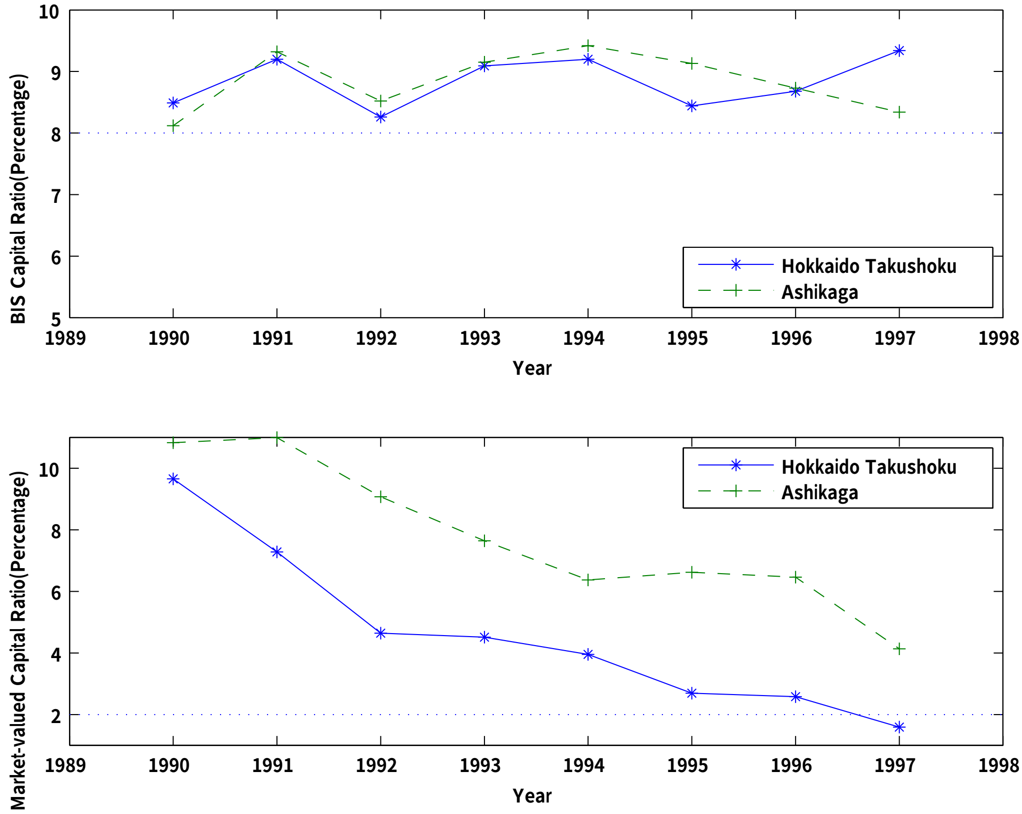
on specific on-balance-sheet credit holding. In addition, they are difficult to be manipulated by banks consistently.

In this chapter, we propose a market-valued capital ratio as an indicator to gauge the riskiness of banks to exploit the appealing features discussed above. Shimizu (2004, 2005) take the initiative in Japan to analyze the dynamic movement of the market-valued ratio for individual banks, and then conclude that the market-valued capital ratio is a more accurate measure of bank soundness than the BIS capital ratio. Shimizu(2007a, 2007b) make the similar point by further stressing the divergence between market-valued capital ratios and BIS capital ratios for Japanese banks. Following Shimizu(2007a, 2007b), Fig (4.1) compares the behavior of both the BIS capital ratios and the market-valued capital ratios[5] for two Japanese banks in the 1990's: one is Hokkaido Takushoku Bank, which failed at Nov 1997, the other is Ashikaga Bank, which suffered bank run in Autumn 1997 and then received government rescue money. It is clear that both banks kept the BIS capital ratio above 8% even right before the events, while the market-valued capital ratio started to fall at early stage to indicate the riskiness. Hokkaido Takushoku Bank finally went into bankruptcy with market-valued capital ratio below 2%. Of course, example themselves can never be convincing. This chapter then provides empirical evidence on the question about whether the market-valued capital ratio or the BIS capital ratio is better at identifying risky banks by looking at the relation between different measures of capital

[5]The market-valued capital ratio is defined as the market value of equity divided by bank's total assets. See below for more detail definition.

ratios and average returns of bank stocks. Empirical evidence suggests that the market-valued capital ratio rather than the BIS capital ratio could be a more informative indicator to identify risky banks.

Figure 4.1: Capital Ratios for Two Troubled Japanese Banks in 1990s



The rest of the chapter is organized as follows. The next section presents the main hypothesis. Section 3 describes the data and methodology. Section 4 reports the empirical results. Section 5 documents the empirical relation between capital ratios and risk factors, and capital ratios and operating performance. The final section concludes.

4.2 Main Hypothesis

This study examines the question about whether the market-valued capital ratio or the BIS capital ratio is better at identifying risky banks by looking at the relationship between different measures of capital ratios and average returns of bank stocks. Our idea is based on the relation between risk and expected return. Asset pricing theory has taught us that systematic difference in average returns are due to difference in risk, provided stocks are priced rationally.

The centerpiece of modern asset pricing theory is that the price of a security measures expected discount future payoffs:

$$1 = E_t(m_{t+1} R^i_{t+1}), \tag{4.1}$$

after some algebra, we could rewrite the above equation as follows:

$$E_t(R^i_{t+1}) = R^f_t - cov_t(m_{t+1}, R^i_{t+1})/E_t(m_{t+1}) = R^f_t + \beta^i_{m,t}\lambda_{m,t}, \tag{4.2}$$

where R^i_{t+1} represents the return of asset i from time t to $t+1$, R^f_t denotes the risk-free rate known in advance, m_{t+1} is the stochastic discount factor. $\lambda_{m,t} \equiv var_t(m_{t+1})/E_t(m_{t+1})$ is the price of risk and $\beta^i_{m,t} \equiv -cov_t(m_{t+1}, R^i_{t+1})/var_t(m_{t+1})$ is the quantity of risk in each asset i.

The equation (4.2) shows that it is exactly the covariance of an asset's payoffs with the stochastic discount factor that measure risk and generate risk premium in financial markets. Economists come up to find that useful measures of the stochastic discount factor are related to macroeconomic events such as aggregate consumption, recession, or financial distress factors.[6] Therefore, the risk information impounded in share price is systematic risk in the sense that it links the risk premia to aggregate economy events, such as recession, or financial distress, to indicate what the value of bank shares may be in the case of bad economic time.

Moreover, the excess expected returns reflect both the quantity and price of risk. The quantity of risk would vary from bank to bank, while the price of risk is the same for all banks. Since a huge amount of researches documented that the dynamics of share prices are affected significantly by changing risk prices, we would like to study the cross-sectional variations of bank stock returns to focus mainly on the quantity of risk.

These facts lead us to test the hypothesis that if higher capital ratios indicate lower riskiness, banks with higher capital ratios would earn lower average returns. In other words, capital ratios should associate negatively with average returns.

Hypothesis 1 *Banks with higher capital ratios have on average lower subsequent stock returns than banks with lower capital ratios.*

[6]While the traditional theories such as CAPM and APT measure the stochastic discount factor by the behavior of large portfolio assets, economists now become focusing on the fundamental determinants of the stochastic discount factor. See Cochrane (2008b) for a survey linking financial markets to the real economy.

In sum, there are mainly three features in our analysis. First, we would extract risk information of banks from stock prices based on the asset pricing theory.[7] Second, we would like to exploit the information from the cross-sectional variations of stock returns to focus mainly on the quantity of risk rather than studying the dynamics of bank stock returns. Third, we would exploit the difference between market-valued capital ratios and BIS capital ratios and see which is better at identifying risky banks.

4.3 Data and Methodology

As indicated in the previous section, we study the empirical relationship between average stock returns and several capital ratios to test the hypothesis that if higher capital ratios indicate lower riskiness, banks with higher capital ratios would earn lower average returns. In particular, we would like to examine stock returns of banks in retrospect, and see if several forms of capital ratios of banks are associated with subsequent realized average returns, and how they are related with average returns, by using Japanese listed bank's data from 1990 through 2008. The first measure of capital ratio is the stan-

[7]There are other risk measures used in the literature, such as volatility of stock prices, Z-scores, and ex post estimated probability of failure (Konishi and Yasuda (2004) and Eetrella, Park and Peristiani (2000)), which are not considered here. Risk priced in financial markets could be relevant to policy making, since banks with high risk priced in the financial market are those who do badly (in the worst case even go into bankruptcy) in bad times such as when the banking system, or the whole economy is in trouble.

dard measure defined by the BIS capital adequacy rules. The BIS capital ratio (*BIS*) is the BIS capital divided by the bank's risk-weighted assets. In addition, we propose two capital ratio measures based on the market-valued capital. First, the market-valued leverage ratio (*MLR*) is defined as the market value of equity divided by bank's total assets. Second, the market-valued risk-weighted capital ratio (*MCR*) is the ratio of market value of equity to the bank's risk-weighted assets.[8] We calculate the market value of equity as the number of outstanding shares times the stock price. Our database includes all domestic commercial banks listed in the Tokyo Stock Exchange (TSE) from the year of 1990 through 2008. Our sample covers 1396 observations, while sample size would vary from year to year. All the data used in our analysis came from Nikkei Financial Quest database.

There are two approaches widely used by researchers to identify the relationship between the cross-section of stock returns and variables of interest. The first approach is to form portfolios based on sorts of variables of interest. The sorting approach is not only easy to perform, but could also provide us an intuitive and very clear examination about how bank's average returns would vary with our measures of capital ratios. However, this approach may suffer from potential problems. The sorting results would depend on the weight to which we assign on each bank. When forming equal-weighted portfolios, the sorting results tend to be dominated by small regional banks, simply because there are much more observations of small regional banks than large

[8]MCR and BIS have the same denominator part, but different numerators.

city banks. On the other hand, large city banks are more likely to dominate the sorting results, when we form value-weighted instead of equal-weighted portfolios. In order to provide a more balanced picture of the relation between our measures of capital ratios and the cross-section of stock returns, we would accompany equal-weighted results along with value-weighted results.[9] Finally, we also provide results by excluding trust banks from our sample, or restricting sample period from 1994 to 2007, to show the pervasiveness of the empirical relation between our measures of capital ratios and average returns.[10]

In particular, average returns are calculated as follows: Bank stocks were first sorted into three portfolios of ascending order by using each measure of capital ratios at the end of each year's June respectively. We calculate *MLR* and *MCR* as market value of equity at the end of June of year t, divided by total assets and risk-weighted assets at the end of March of year t respectively. The BIS capital ratio (*BIS*) is calculated from the corresponding balance-sheet data at the end of March of year t. Since most banks listed in the TSE

[9]Unfortunately, we could not afford to pursue the pervasiveness of the relation directly by dissecting large city banks from small regional banks, due to the limited number of large city banks. We confirm that the result from small regional banks alone is not qualitatively different from others. We do not report the result here to save space.

[10]The sub-sample excluding trust banks reflects the fact that trust bank's business could be somewhat different from other commercial banks. We restrict sample period from 1994 to 2007 to accommodate two facts: the step-by-step measures of the implementation of BIS capital adequacy requirement (Keikasochi) until 1993, and the transition to BIS 2 since 2007.

have fiscal year ending in March, we assume that three months is enough for financial information that we use in forming portfolios to be publicly available. We rank all banks in each year's sample based on different capital ratio measures, and then calculate 30 percent and 70 percent breakpoints for each measure. We then place all banks into three portfolios. The banks below the 30 percent break-point are assigned to the first portfolio (Low); the middle 40 percent of banks are assigned to the second portfolio (Medium); and banks above the 70 percent break-point are assigned to the third portfolio (High). We then recorded the return of each portfolio over the following year from the beginning of July through next June. We calculate the stock returns by incorporating the effect of stock splits and dividends. We repeat this sorting procedure and make portfolio reformations at the end of each year's June over the sample period from the year of 1990 to 2008. We could then examine the average return of each portfolio sorted on different measures of capital ratios.

Other than intuitive portfolio sorting approach, we also perform a more formal year-by-year cross-sectional regression analysis of returns on capital ratios, in the spirits of Fama and MacBeth (1973), to confirm our earlier sorting results. The regression approach could help us drawing formal inferences about the relationship between the average returns and capital ratios by imposing a functional form between them. We would apply the regression forecast to individual banks rather than portfolios. In other words, we would apply the following regression forecast to individual banks to see whether the variable $x_{i,t}$ representing several measures of capital ratios would have significant coefficients b, and check if the sign of the coefficients are consistent with our results above. The regression may suffer potentially from influential observation problems, since stock returns on individual banks can be extreme. The two approaches thus provide a cross-check for each other to see if we yield consistent conclusions.

In particular, we would first run a cross-sectional regression at each year, instead of estimating a single cross-sectional regression with the sample averages over time. Note that forecast errors in our regressions are orthogonal to forecasters.[11]

$$R_{t+1}^i - R_t^f = a_t + b_t \cdot x_{i,t} + \epsilon_{i,t+1}, \tag{4.3}$$

where $R_{t+1}^i - R_t^f$ is the return of bank i in excess of risk-free rate over the period t to $t+1$. We then obtain the estimate of $\hat{b}$ as the average of the cross-sectional regression estimates. More importantly, we could also use the standard deviation of the cross-sectional regression estimates to calculate the standard error for the estimate that corrects for the cross-sectional correlations in returns.

[11]Although there may be other relevant predicting variables, we focus on the three capital ratios because our objective is to compare the effectiveness of various capital ratios instead of searching a prediction model.

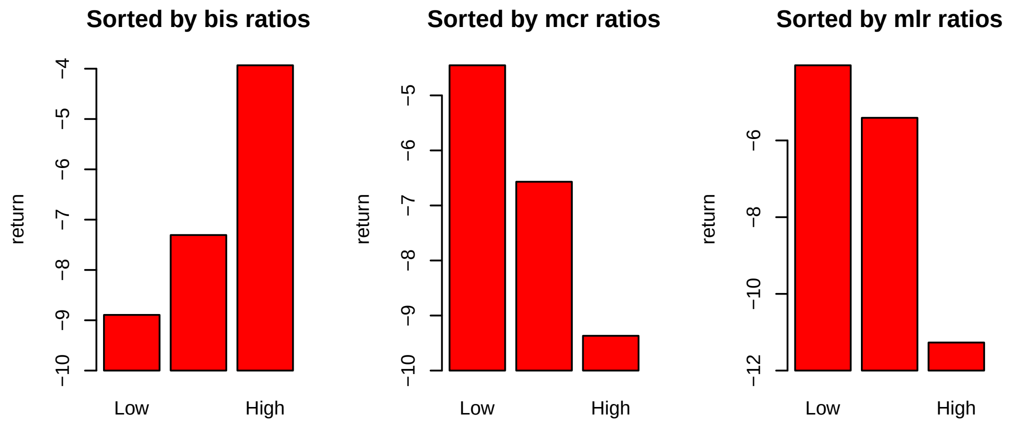
4.4 Empirical Results

The results of average returns for equal-weighted and value-weighted portfolios sorted on each measure of capital ratios are plotted in Figure (4.2). Figure (4.2) also include the result for subsample period from 1994 to 2007. Figure (4.3) shows the empirical results by excluding trust banks. We would focus on the equal-weighted results over the full sample below, since they are essentially no change from others. It is clear that the average returns of portfolios sorted by *BIS* ratios increase monotonically as the *BIS* ratios increases. The BIS capital ratios seem to be positively related with average returns, implying that banks may be risky despite of reporting high BIS capital ratios. On the other hand, when stocks are sorted using market-valued capital ratios, the average returns of portfolios would strictly increase as the associated capital ratios of the portfolio decrease. Panel (A) of Table (4.1) also shows that the difference in average returns between stocks with Low and High capital ratios is quite large.

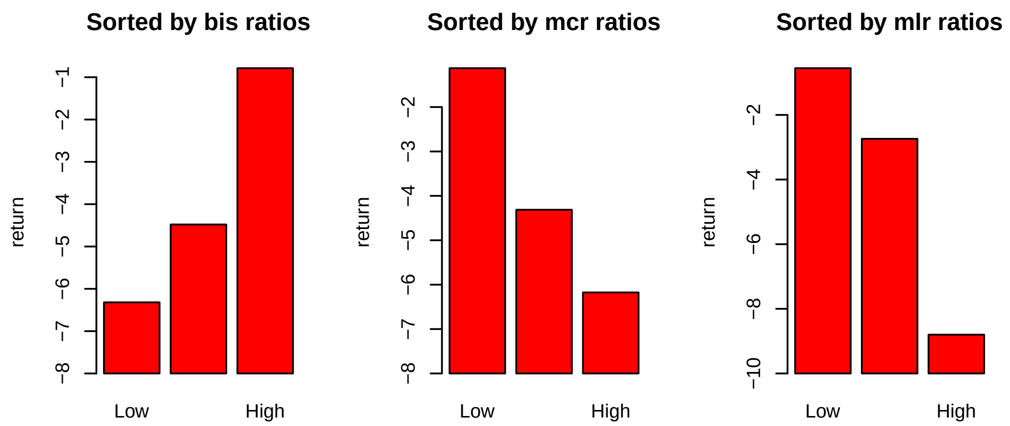
Initially, the results seem to be consistent with the objective of BIS bank regulation that requires banks to hold BIS capital ratio above certain level, because the average stock returns of banks with higher BIS capital ratio indeed have outperformed banks with lower BIS capital ratios. However, the theory suggests that it is those assets with higher risk should offer higher average returns to attract investors to hold them. Therefore, on the second thought, in order to be a successful measure of risk, banks with lower BIS capital ratio should present higher stock returns than banks with higher

Figure 4.2: Average Returns of Portfolios Sorted on Capital Ratios

Panel (A): Average returns of equal-weighted portfolios (1990-2008)



Panel (B): Average returns of equal-weighted portfolios (1994-2007)



Panel (C): Average returns of value-weighted portfolios (1990-2008)

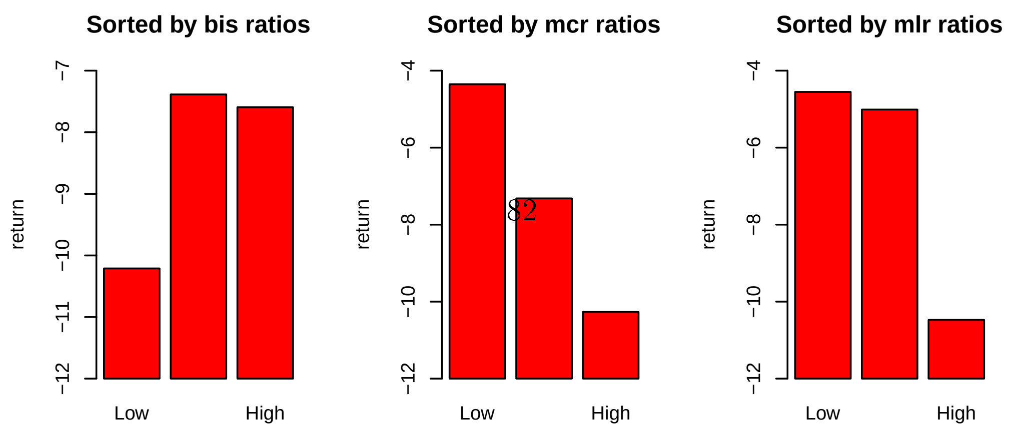
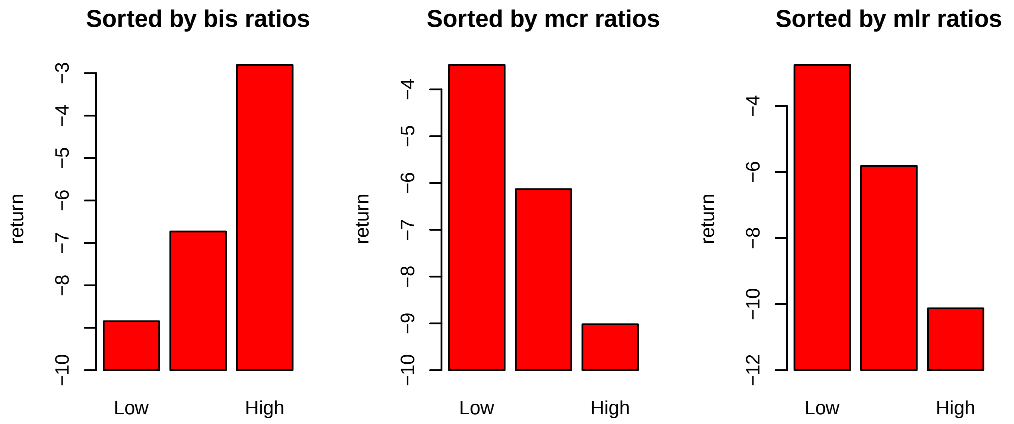
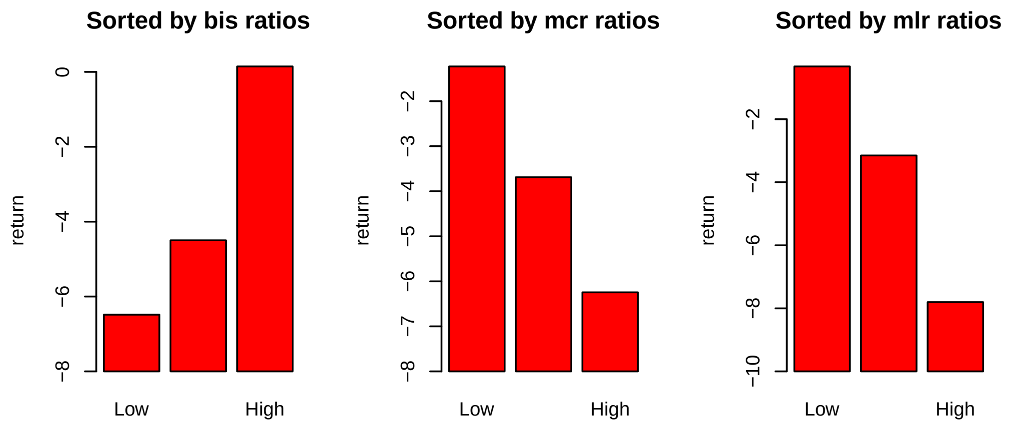


Figure 4.3: Average Returns of Portfolios Sorted on Capital Ratios (Trust Banks Excluded)

Panel (A): Average returns of equal-weighted portfolios (1990-2008)



Panel (B): Average returns of equal-weighted portfolios (1994-2007)



Panel (C): Average returns of value-weighted portfolios (1990-2008)

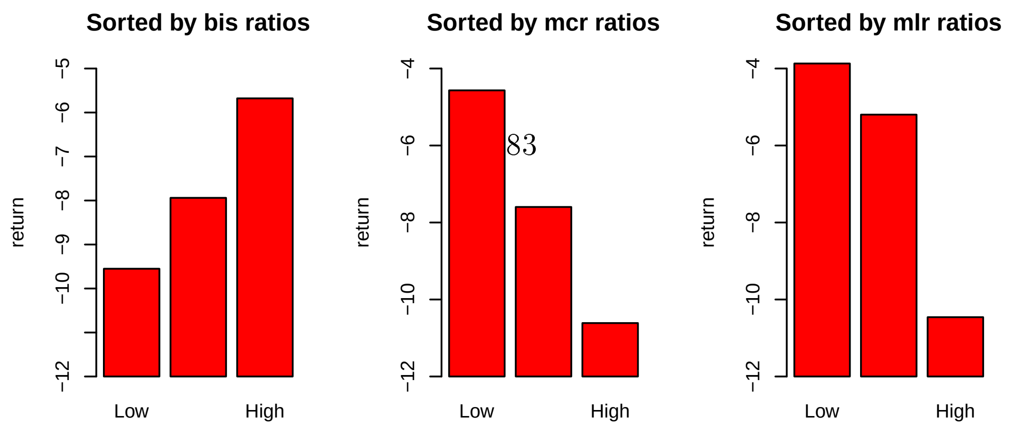


Table 4.1: Average Returns of Portfolios Sorted by Capital Ratios and FM Regression Statistics

	BIS ratios	Market ratios	
	BIS	*MCR*	*MLR*
Panel A: Spread of average returns between High and Low portfolios			
All listed banks included	4.96	6.03	8.39
Trust banks excluded	6.04	5.54	7.37
Panel B: Slope coefficients and standard errors from Fama-MacBeth regression			
All listed banks included	1.72*	-0.92*	-1.56*
	(0.83)	(0.39)	(0.55)
Trust banks excluded	1.77*	-0.91*	-1.66*
	(0.85)	(0.40)	(0.59)

Note: Panel (A) reports the resulting difference in equal-weighted average returns between Low and High portfolios sorted on each measure of capital ratios. The BIS capital ratio (*BIS*) is the BIS capital divided by the bank's risk-weighted assets. The market-valued leverage ratio (*MLR*) is defined as the market value of equity divided by bank's total assets. The market-valued risk-weighted capital ratio (*MCR*) is the ratio of market value of equity to the bank's risk-weighted assets. Panel (B) reports the Fama-MacBeth regression results. We use annualized call rates to measure risk-free rates. * indicates significant level at the 5%. Numbers in parenthesis are FM standard errors.

BIS capital ratios. While the BIS capital ratio fails to present this relation, market-valued capital ratios seem to capture the pattern quite successfully by showing significant negative relations with average returns. Higher average returns imply higher risk priced in the stock market, provided stocks are not mis-priced systematically and persistently. Therefore, market-valued capital ratios rather than BIS capital ratios may serve as a better indicator of identifying risky banks.

Panel B of Table (4.1) shows the results of slope coefficients and standard errors from the Fama-MacBeth regression of returns on several capital ratio measures. We could confirm our results from sorting procedure: the coefficients for *BIS* ratios are positive and statistically significant, while the coefficients for two market-valued capital ratios are significantly negative. Note that we are not assuming cause on the right and effects on the left hand. Our forecasting regressions are essentially about how the market-valued capital ratio is formed. In other words, the cross-sectional variation in market-valued capital ratios reveals the information about the market's expectation about difference in discount rates, or difference in expected returns causes variation in market-valued capital ratios.[12] In sum, our results from both portfolio sorting and formal regressions support that market-value-capital ratios associate negatively with average returns, while the BIS capital ratio, on the other hand, appears to be positively related with average returns.

[12] Welch (2004) also documents that stock returns are a first-order determinant of market-based debt ratios.

4.5 Additional Results

Given that the empirical evidence about the negative relations between average stock returns and market-valued capital ratios is consistent with our hypothesis, we are now in a position to explore 1) whether market-valued capital ratios proxy for sensitivity to risk factors; 2) whether market-valued capital ratio's pattern in returns are consistent with the behavior of operating performance.

4.5.1 Capital Ratios and Risk Factors

First, if the relation between average returns and market-valued capital ratios are due to rational pricing, there must be common risk factors in returns related with market-valued capital ratios.[13]. In other words, banks with lower market-valued capital ratios would earn higher future returns than those with higher market-valued capital ratios, not because they are with lower capital ratios, but because there is covariation in returns with common risk factors.

Hypothesis 2 *There are common risk factors in returns related with market-valued capital ratios. In other words, market-valued capital ratios proxy for sensitivity to risk factors.*

[13]This test is in the spirit of seminal work by Fama and French (1993, 1996). They showed that there are common risk factors in returns associated with firm size and book-to-market equity for non-financial corporations.

Therefore, we would like to check whether the dispersions in average returns across capital ratio-sorted portfolios are also associate with variation in slope coefficients on risk factors. In particular, we employ a two-factor model to help explain the cross-section of average returns: an overall market factor and a mimicking portfolio factor related to market-valued capital ratios[14]:

$$R_i(t) - R_f(t) = \alpha_i + \beta_i(R_m - R_f) + \gamma_i LMH(t) + e_i(t), \tag{4.4}$$

where $R_i(t) - R_f(t)$ is the equal-weight excess portfolio returns sorted by market valued capital ratios. $R_m(t) - R_f(t)$ is the excess market return calculated as the value-weighted return on all TSE stocks minus the risk-free rate. $LMH(t)$ factor is constructed using value-weighted portfolios formed on the market-valued capital ratio (MLR): the average return on the portfolio with Low market valued capital ratios minus the average return on the portfolios with High market valued capital ratios.

You could see from the table (4.2) that the two-factor model could help explain cross-sectional variations in average returns. The model shows economic significance that the pattern of regression coefficients β_i and γ_i are roughly in line with average returns relation in Figure (4.2). The intercept terms are usually interpreted as the abnormal return left unexplained by the exposure to the risk factors. After adjusting for risk exposure to the factors,

[14]We find that the parsimonious two factor model works better than the CAPM and FF three-factor model. We may still be able to search other sensible risk factors that help explain the cross-section of average returns. And we need economic models that explain why those factors get risk premium. However, it is not the main task of the chapter.

Table 4.2: Capital Ratios and Risk Factors

Regression: $R_i(t) - R_f(t) = \alpha_i + \beta_i(R_m - R_f) + \gamma_i LMH(t) + e_i(t)$

	Sorted by MCR ratios			Sorted by MLR ratios		
	Low	Medium	High	Low	Medium	High
α_i	0.008	-0.015	-0.029	0.009	-0.007	-0.040
	(0.026)	(0.025)	(0.021)	(0.025)	(0.023)	(0.028)
β_i	0.728*	0.573*	0.594*	0.700*	0.520*	0.693*
	(0.080)	(0.066)	(0.076)	(0.069)	(0.068)	(0.081)
γ_i	0.257*	-0.072	-0.278*	0.264*	-0.080	-0.274*
	(0.105)	(0.090)	(0.083)	(0.100)	(0.076)	(0.123)
R^2	0.801	0.785	0.822	0.842	0.730	0.829

Note: * denotes significance at the 5% level. In parenthesis are heteroskedasticity-autocorrelation robust standard errors. $R_i(t) - R_f(t)$ is the test portfolio return sorted by market valued capital ratios. $R_m(t) - R_f(t)$ is the excess market return calculated as the value-weighted return on all TSE stocks minus the risk-free rate. We use annualized call rates to measure risk-free rates. $LMH(t)$ factor is constructed using value-weighted portfolios formed on the market-valued capital ratio (MLR): the average return on the portfolio with Low market valued capital ratios minus the average return on the portfolios with High market valued capital ratios.

the estimated intercepts are small and insignificant statistically. Overall, the results indicate that the difference in average stock returns could be largely explained by differences in exposure to risk. Therefore, the evidence that market-valued capital ratios proxy for sensitivity of risk factors is consistent with our rational-pricing story for the market-valued capital ratio's pattern in average returns. However, this test is silent on why market-valued capital ratios are related to risk factors in returns.

4.5.2 Capital Ratios and Operating Performance

Then, we explore the cross-sectional variation of operating performance across portfolios to help understand the economic reasons why market-valued capital ratios are related to risk in returns. The five measures of operating performance are as follows: the return on equity (ROE) defined as pretax profits divided by book equity, the return on assets (ROA) defined as pretax profits divided by book assets, the net profit margin (NPM) defined as pretax profits divided by total gross earnings, the earnings ratios (ER) defined as earnings from lending and other risky security holdings divided by total gross earning, the non-performing loan ratio ($NPLR$) is defined as the sum of loans to bankruptcy borrower, loans with risk to watch borrower and loans to intensive controlled borrower divided by total balance of loans. The first three measures are commonly considered as indicators of bank profitability. The forth measure indicates the business model of a bank, while the fifth measure is the traditional balance-sheet-based indicator of the quality of bank lending.

We provide a simple model modified from Fama and French (1995) to help understand the relation between profitability and market-valued capital ratios of banks. Suppose a bank paying out cash flow (C_t) in year t, which equals to pretax profits minus taxes (T_t) and other outlays (I_t) than payout to shareholders. We also assume that at year t the expected taxes and other outlays for any year $t+i$ are proportional to expected profits,

$$\begin{aligned} E_t C_{t+i} &= E_t[P_{t+i} - T_{t+i} - I_{t+i}] \\ &= E_t[(1-\lambda_1-\lambda_2)P_{t+i}], \end{aligned} \tag{4.5}$$

where λ_k (k=1,2) denotes the proportional factors for taxes and outlays respectively. Presuming the discount rate at time t is r_t, the market value of equity (ME) of the bank at year t would be

$$ME_t = \sum_{i=1}^{\infty} \frac{E_t C_{t+i}}{1+r_t^i} = (1-\lambda_1-\lambda_2) \sum_{i=1}^{\infty} \frac{E_t P_{t+i}}{(1+r_t)^i}. \tag{4.6}$$

This implies that the market-valued of capital ratio (ME/BA) is

$$\frac{ME_t}{BA_t} = (1-\lambda_1-\lambda_2) \sum_{i=1}^{\infty} \frac{E_t[P_{t+i}/BA_t]}{(1+r_t)^i}. \tag{4.7}$$

This model implies that it is those banks required to pay higher returns at the market will have lower market-valued capital ratio. The evidence of negative relation between average stock returns and market-valued capital ratios presented at the previous section is consistent with the implication of the simple model. This model also implies another testable hypothesis that higher market-valued capital ratios are associated with persistently higher profitability, while lower market-valued capital ratios are related with persistently lower profitability.

Hypothesis 3 *Banks with higher market-valued capital ratios are persistently more profitable than banks with lower market-valued capital ratios.*

The results from the portfolio sorting procedure in Figure (4.4) show that banks with higher capital ratios tend to have higher profitability whether measured by return on equity, return on assets, or net profit margin. The evidence here demonstrates that the behavior of stock prices, in relation to market-valued capital ratios, is indeed consistent with the behavior of profitability. Following Fama and French (1995), we would also examine the average profitability of banks with high and low market-valued capital ratios for 7 years around the portfolio formation. Figure (4.5) shows that market-valued capital ratios are associated with persistent differences in profitability. Banks with higher market-valued capital ratios are on average more profitable than lower market-valued capital ratio banks for 7 years around the portfolio formation year.

Moreover, banks with higher *BIS* capital ratios have similar earning performance as to banks with higher market-valued capital ratios. On the other hand, investing in banks with higher *BIS* capital ratios would earn much higher expected returns than banks with higher market-valued capital ratios. Our risk-return relationship lead us to expect that bank portfolios with similar earnings but lower discount rate would have higher market-valued capital ratios. It is exactly what we found in the data.

Finally, although banks with higher capital ratios seem to have slightly lower earnings ratio, we find that bank are similar to each other in business model in the sense that they all heavily depend on the revenues from traditional banking business of lending and security holdings. Revenues from lending and other risky security holdings roughly consist of about 80% of their total gross earnings. Therefore, it is probably the quality instead of quantity of their risky lending and security holding business that make a profound difference to riskiness of banks. Moreover, we find that non-performing loan ratios are indeed negatively associated with capital ratios. However, the dispersions of non-performing loan ratios across portfolios are quite limited, just about one percentage point for the long-short positions of extreme portfolios. Therefore, it seems to remain as an open question for future studies to examine what aspects other than the reported non-performing loan ratios could help identify the quality of bank lending.[15]

4.6 Conclusion

Our empirical research investigates the relationship between different capital ratios and the cross-section of stock returns in banking industry by using Japanese listed bank's data from 1990 through 2008. The results show that market-valued capital ratios associate negatively with average returns, while

[15] Knaup and Wagner (2009) have proposed a new method of measuring the quality of bank's credit portfolios based on the information impounded in bank share prices rather than balance-sheet data.

Figure 4.4: Capital Ratios and Operating Performance

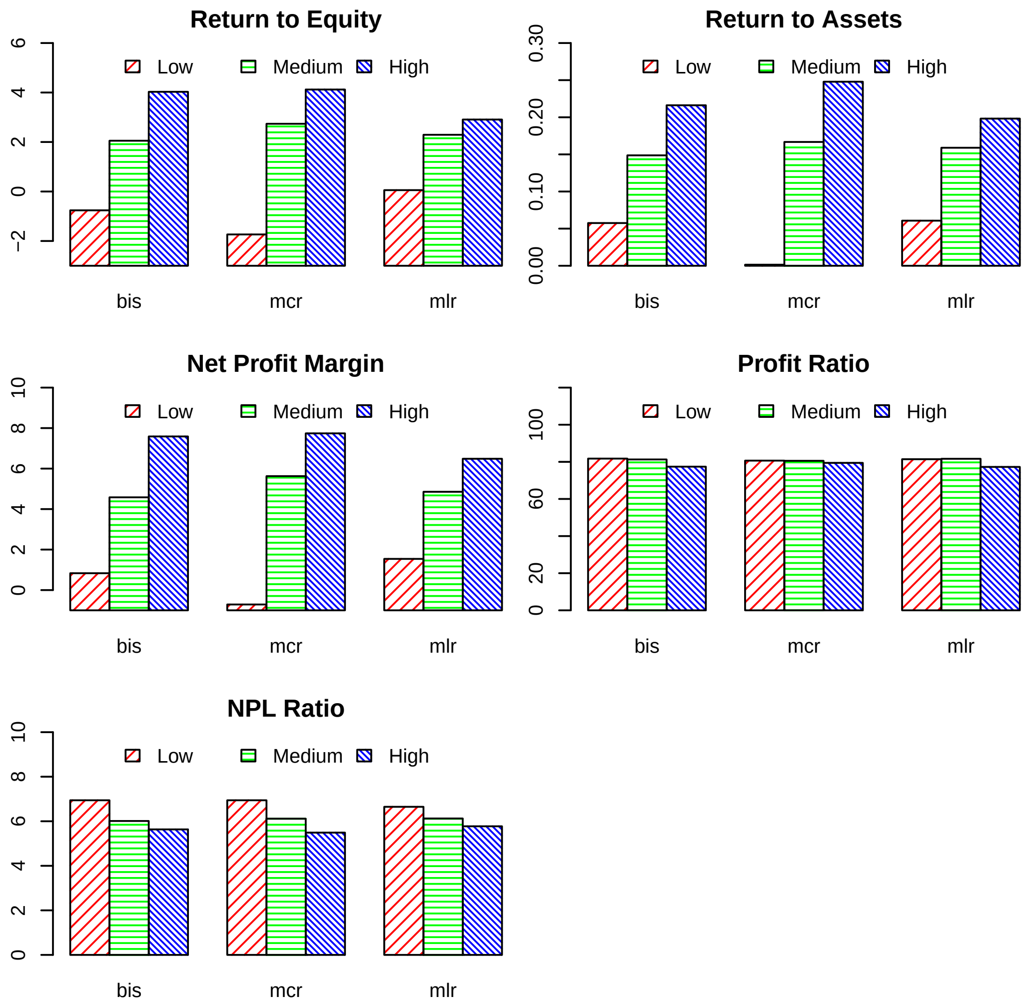
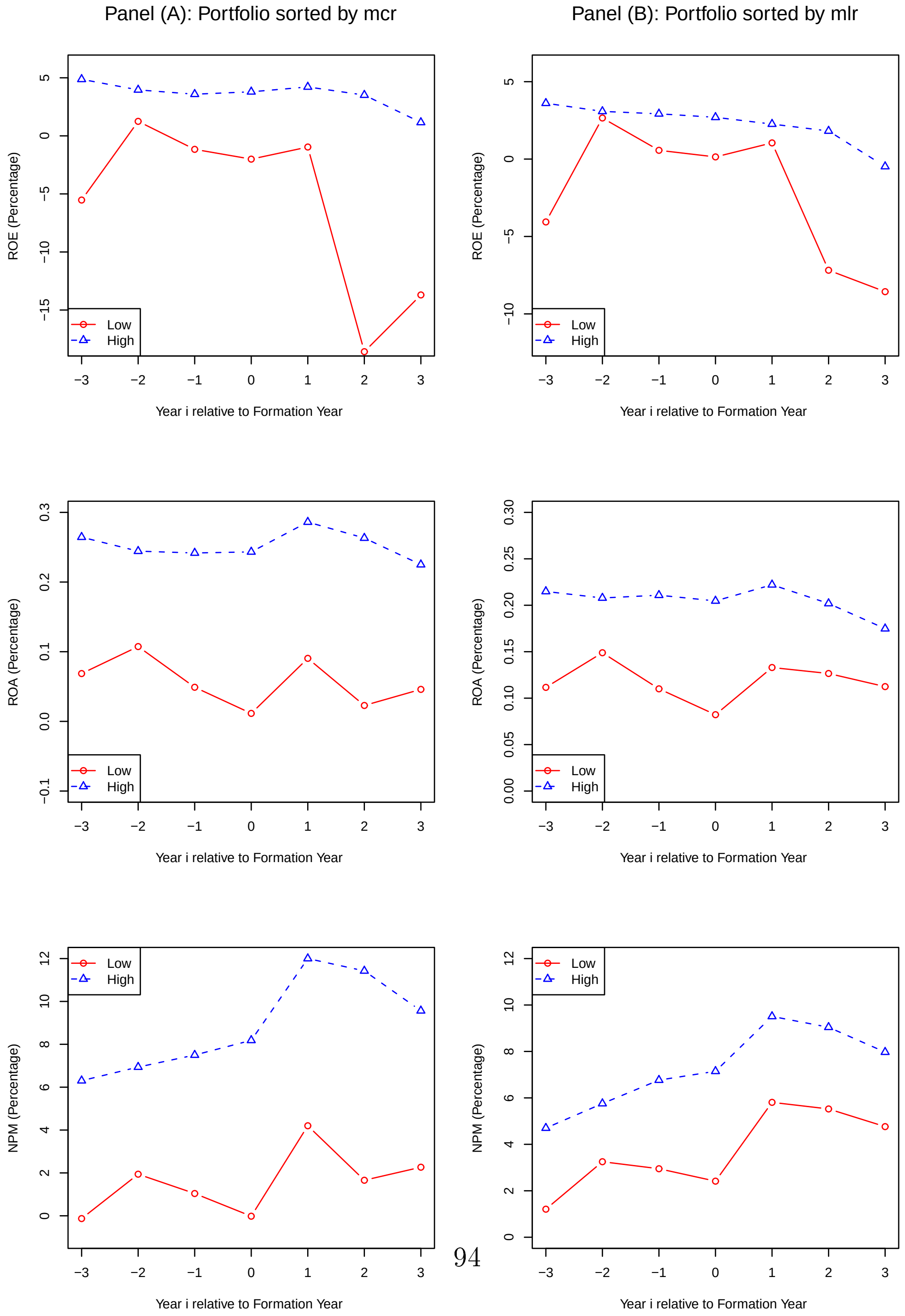


Figure 4.5: The 7-year Evolution of Profitability for Portfolios formed in June of Year t



Note: For each portfolio formation year t 1990 to 2007, the profitability measures (ROE,ROA,and NPM) are calculated for $t+i$, $i = -3, \ldots, 3$. Those profitability measures for year of $t+i$ are then average across portfolio formation year t.

the BIS capital ratio, widely used by bank regulators, is showed to be positively related with average returns. These facts imply that banks may be risky despite of reporting higher BIS capital ratios. On the other hand, the market-valued capital ratios seem to serve as an informative indicator to identify risky banks. In addition, we investigate whether there are common risk factors in returns related with market-valued capital ratios. If the negative relation between average returns and market-valued capital ratios are due to rational pricing, there must be common risk factors in returns related with market-valued capital ratios. We show that market-valued capital ratios proxy for sensitivity to risk factors that capture common variation in returns. We then examine the cross-sectional variation of operating performance across banks with capital ratios to explore the economic reasons why market-valued capital ratios are related to risk in returns. The results show that low market-valued capital ratio signals persistently poor profitability whether measured by return on equity, return on assets, or net profit margin. We also find that it is quality instead of quantity of risky lending and security holding that make a profound difference to riskiness of banks. However, the dispersions in non-performing loan ratios seem not to be informative enough to identify the quality of bank lending.

Rather than proposing a market-valued capital ratio as one all-encompassing measure, we are expecting that it could be one of a list of potentially useful indicators to guide regulator's actions to evolving problems. In addition, our analysis also suggests that regulatory structure may not be a substitute for market discipline, since regulators could obtain comprehensive and timely information by monitoring market-based indicators. Therefore, it makes sense for regulators to enhance market discipline rather than replacing it. Finally, we still need economic models to help understand what drives the variation in market-valued capital ratios.

Chapter 5

What Drives the Time-Series and Cross-Sectional Variations in Bank Capital Ratios

5.1 Introduction

Capital adequacy for commercial banks has long been received considerable attention in the finance literature. However, most previous studies on this issue have been focused on the book values of capital, possibly due to the overwhelming attention paid to book values by bank regulators. As evident in the financial turmoil, the book values of capital may not provide good estimates of buffer preventing a bank from insolvency when its asset value falls. Moreover, there has also been changes in the practice of bank capital regulation beyond the use of simple leverage ratios based on book values of capital. The Basel accord negotiated among G10 countries has require banks to maintain their risk-weighted capital ratios above certain level. Although the prevailing BIS capital regulation framework has been mainly concentrated on the elaboration of the asset part, it indicates that the regulators may be aware of the deficiencies in book values of capital. In fact, many considerations used in calculating the risk-weighted assets in the BIS framework are precisely related with the factors underlying the market valuation of a bank. Furthermore, the new BIS II framework has also advocated to enhance the market discipline as one of its three pillars.

Although most previous literature and bank regulators have focused on book values of bank capital, some economists have previously proposed of using market equity values to measure bank's capitalization (e.g. Marcus 1983, Keeley 1990, Shimizu 2007, Flannery and Rangan 2008).[1] It is argued that market equity values measure the amount of capital that shareholders are willing to offer for a bank, therefore provide better estimates of the protection afforded by capital. This paper would follow this string of researches to focus on the market-valued capital ratios and investigate the underlying forces driving their time-series and cross-sectional variations.

Few papers have been focusing on the time-series and cross-sectional variations in bank capital ratios based on the market values of equity. Marcus

[1] It has also been a tradition to use market values of capital to measure the ownership of stock holders in capital structure literatures (e.g. Welch 2004).

(1983) documents a dramatic decline of market-valued capital ratios in U.S. commercial banks during 1960s and 1970s. He find negative relation between capital ratios and the interest rates and, and claim that the fall in capital ratios could be largely attributed to the rise in interest rates. Flannery and Rangan (2008) recently documents a sharp increase in market-valued capital ratios of large U.S. banks in 1990s, and suggests several factors including bank profitability, regulatory capital ratios, stock market appreciation, and especially changes in bank risk triggered by weakened conjectural government guarantees in the early 1990s could help explain the the capital build-up. Shimizu (2004, 2005) take the initiative in Japan to propose a market-valued capital ratio and analyzes carefully the dynamic movement of market-valued capital ratios for individual Japanese banks. Shimizu(2007a, 2007b) further suggest that the market-valued capital ratio could be a more appropriate measure of bank soundness by stressing the divergence between market-valued capital ratios and BIS capital ratios. On the other hand, the cross-sectional variations in bank capital ratios are related to the cross-sectional variation in average stock returns. Chen (2009) presents evidence by using data of Japanese banks that banks with higher capital ratios have on average lower subsequent stock returns than banks with lower capital ratios. He also shows that the cross-sectional variation in bank capital ratios are associated with the cross-sectional variations in profitability. Banks with higher market-valued capital ratios are persistently more profitable than banks with lower market-valued capital ratios.

Capital ratios vary over time and across banks. Intuitively, both expected stock returns and expected future profitability could influence the determination of bank capital ratios. We add to the literature by providing an overall framework on how theses factors combine to explain the time-series and cross-sectional variations in capital ratios. While book values are inherently backward looking, capital ratios based on market values are generally forward looking. It is therefore important to capture this feature into our considerations in investigating the driving forces of variations in capital ratios.

In addition, although previous works have pointed out that capital ratios could be affected by either profitability or stock returns, no existing research has ever provided quantitative assessment about the roles played by these factors in the determination of bank capital ratios. We aim to fill the gap by identifying quantitatively the relative importance of these factors in determining both the time-series and cross-sectional variations in bank capital ratios. In this paper, we document the time-series and cross-sectional variations of Japanese bank's capital ratios and investigate their underlying driving forces. In particular, by adapting the log-linearized present-value model developed by Campbell and Shiller (1988) and Vuolteenaho (2000), we would be able to decompose the variations in capital ratios into three components: the variations in expected future discount rates, future profitability and future leverage ratios. This decomposition allows us to conduct the variance decomposition to show exactly how much the variations in expected future discount rates and future profitability have contributed to the variations in bank capital ratios respectively. The results show that the expected future discount rates dominate the time-series variation in bank capital ratios, while the expected future profitability has played an almost equally important role as the expected discount rates in the cross-sectional variations.

The rest of the paper is organized as follows. Section 2 describes the data with the documentation about the time-series and cross-sectional variations in bank capital ratios. Section 3 presents the log-linearized present-value model for the decomposition of capital ratios. Section 4 reports the time-series variance decomposition results. Section 5 reports the cross-sectional variance decomposition results. Section 6 concludes.

5.2 Data

5.2.1 Basic Data

Our basic data comes from the intersection of two database included in NEEDS-FinancialQUEST from 1977 to 2009: one is the Corporate Finance Database, and the other is the Stock Database. The Stock Database contains daily stock prices, realized dividend yields for all listed Japanese commercial banks. The Corporate Finance Database includes shares outstanding, dividends, and other relevant accounting information for all Japanese commercial banks. All the data used in our analysis are in annual frequency.

5.2.2 Variable Definitions

We define all variables on per share basis[2]. We measure the market equity (M_t) of a bank as share price at the end of June. The capital ratios (CR_t) are then computed as the ratio of market equity in year t divided by the total assets per share for the last fiscal year ending in March of year t. We measure a bank's profitability as accounting returns on equity ($\mathrm{ROE}_t = Y_t/B_{t-1}$), which is calculated as the ratio of earnings per share (Y_t) for the fiscal year ending in March of year t to the last fiscal year's book value of total equity per share (B_{t-1}) ending in March of year $t-1$.

We construct simple gross stock returns as the sum of gross returns without dividends and dividend yields. In particular, we calculate the gross returns without dividends as price ratios by incorporating the effect of stock splits and merges.We find dividend yields as the product of gross returns without dividends and realized dividend yields: $\frac{D_{t+1}}{M_t} = \frac{M_{t+1}}{M_t}\frac{D_{t+1}}{M_{t+1}}$. By combining the gross returns without dividends and dividend yields, we can acquire the simple gross stock returns ($R_{t+1} = \frac{M_{t+1}+D_{t+1}}{M_t}$) for each bank.[3] The annual stock returns are recorded from the beginning of July to the end of June.

To be included in our sample, a bank must have stock prices available for June of year t, and the relevant accounting information for the last fiscal year ended at March of year t. We also screen out banks with negative book equity, which are rare in our sample. Finally, we choose 1977 as the start

[2]It is to consistent with our valuation model in section 3.

[3]The simple net stock returns (RET_{t+1}) are then computed as $R_{t+1} - 1$.

date for our analysis simply because it is the longest merged sample we can acquire for both the Stock Database and Corporate Finance Database.

5.2.3 Descriptive Statistics

Table (5.1) shows the descriptive statistics for capital ratios, profitability, and stock returns. In particular, this table reports means, standard deviations, and percentiles for each corresponding variable. We calculate the descriptive statistics from the pooled panel data set from 1977 to 2009 for all banks, city banks, and regional banks respectively. Thus, the numbers reported here capture both cross-sectional and time-series information in our sample.

It is worth of noting some notable features presented in the descriptive statistics. First of all, it is interesting to see that very few (less than 5%, a little above 1%) of the banks in our sample have capital ratios below 2%. As emphasized by Shimizu (2007), all the failed Japanese banks have capital ratios less than or about 2%. Therefore, these numbers suggest that low capital ratios around or below 2% may be serving as an indicator of very high risk for banks. Moreover, the capital ratios of city banks are not only a little higher on average than regional banks, they are also more volatile than regional banks. Similarly, while the stock returns for city banks are much higher than regional banks on average, they are also more volatile. Finally, the standard deviations of accounting returns on equity are also quite large, although they are not as variable as stock returns.

Table 5.1: Descriptive Statistics

	Mean	SD	5%	25%	Median	75%	95%
Panel A: All Banks							
CR	6.18	3.16	2.73	3.98	5.32	7.50	12.51
ROE	1.46	22.60	-21.88	1.96	4.38	7.09	11.70
RET	3.84	32.41	-34.15	-13.62	-0.33	13.17	66.51
Panel B: City Banks							
CR	7.79	4.42	2.78	4.36	6.70	10.61	16.13
ROE	2.44	31.95	-27.35	2.40	5.93	10.75	16.15
RET	11.94	49.94	-48.45	-15.04	1.20	25.24	106.33
Panel C: Regional Banks							
CR	5.87	2.75	2.72	3.95	5.21	7.10	11.55
ROE	1.27	20.31	-20.14	1.85	4.20	6.67	9.98
RET	2.27	27.52	-31.70	-13.42	-0.49	11.88	47.37

Note: This table reports the descriptive statistics about our dataset, i.e., means, standard deviations, and percentiles (5 percent, 25 percent, median, 75 percent, 95 percent) of capital ratios (CR), accounting returns of equity (ROE), and stock returns (RET). The descriptive statistics are computed from the pooled panel data set from 1977 to 2009, consisting of 2112 bank-years. Panel (A),(B), and (C) report the descriptive statistics for all banks, city banks, and regional banks respectively. All the statistics are measured in percentage.

5.2.4 The Time-Series and Cross-Sectional Variations in Bank Capital Ratios

We document the time-series and cross-sectional variations of bank capital ratios during our sample period form 1977 to 2009. Figure (5.1) shows the dynamic movement of value-weighted capital ratios for all banks, city banks, and regional banks respectively. We calculate the annual value-weighted capital ratios for all banks, city banks, regional banks by using each bank's total market capitalization as the weight.

For the case of all banks, the capital ratio started at 4.34% in 1977, and remained almost constant until 1983. The value-weighted capital ratio of all banks was then set to rise rapidly from 1984, and peaked in our sample at 17.90 in 1987, several years before the Nikkei index reached its climax. Since then, the value-weighted capital ratio almost declined all the way throughout 1990's and early years of this decade. Its lowest point occurred at 3.59 in 2003, when Japanese banking industry had experienced a drastic overhaul with the hope to survive. The three maga bank holding companies also began to show up at that time as a result of the restructuring of Japanese banking industry.

Although the value-weighted capital ratio of all banks showed some signs of recovery after 2003, it deteriorated rapidly since the abrupt onset of sub-prime loan crisis in 2007. At the end of our sample period, the value-weighted capital ratio of all banks stood at 3.62 in 2009, a very low level second to

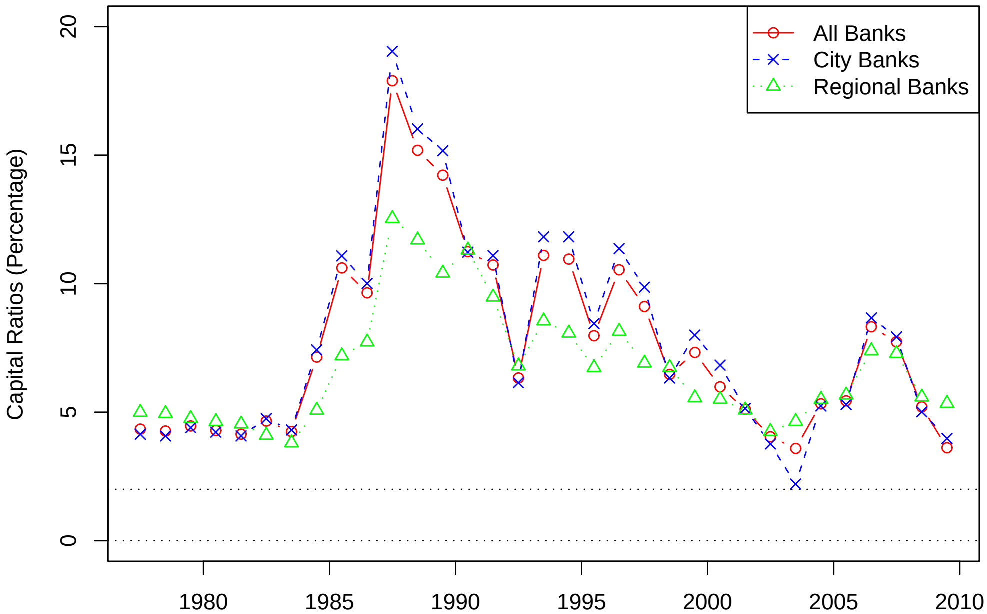


Figure 5.1: The Dynamic Behavior of Capital Ratios (1977-2009)

2003. Many Japanese banks (e.g., MUFG) are now struggling to raise enough capital in the financial market to strengthen their capital ratios. It is also evident that both city banks and regional banks have very similar dynamic movement throughout the sample period.

In addition, we also create 10 value-weighted portfolios by sorting banks on capital ratios in ascending order at the end of June in each year. Figure (5.2) plots the cross-sectional variations of in capital ratios of three representative portfolios over our sample period. You could see that the difference of value-weighted capital ratios between the highest and lowest portfolios are quite large throughout the sample period. The dispersion of capital ratios measured both in the standard deviations and the difference between the highest and lowest portfolios has up and downs many times over the sample period. For example, both the standard deviation and the difference between highest and lowest portfolios reached the peak in 1987 during our sample period, at the level of 4.27% and 13.82% respectively. On the other hand, the lowest point for both the standard deviation and the difference between highest and lowest portfolios occurred at 1983 (about 0.73% and 2.19%). The value-weighted capital ratios of lowest portfolio reached the bottom at the level of 1.17% in 2003, followed by 1.64 at the end of our sample in 2009. In 2009, the value-weighted average of the highest portfolio has a value-weighted capital ratio of 6.25%. The difference between highest and lowest portfolios is 4.61%, while the standard deviation is about 1.31%.

Given the large time-series and cross-sectional variations in capital ratios,

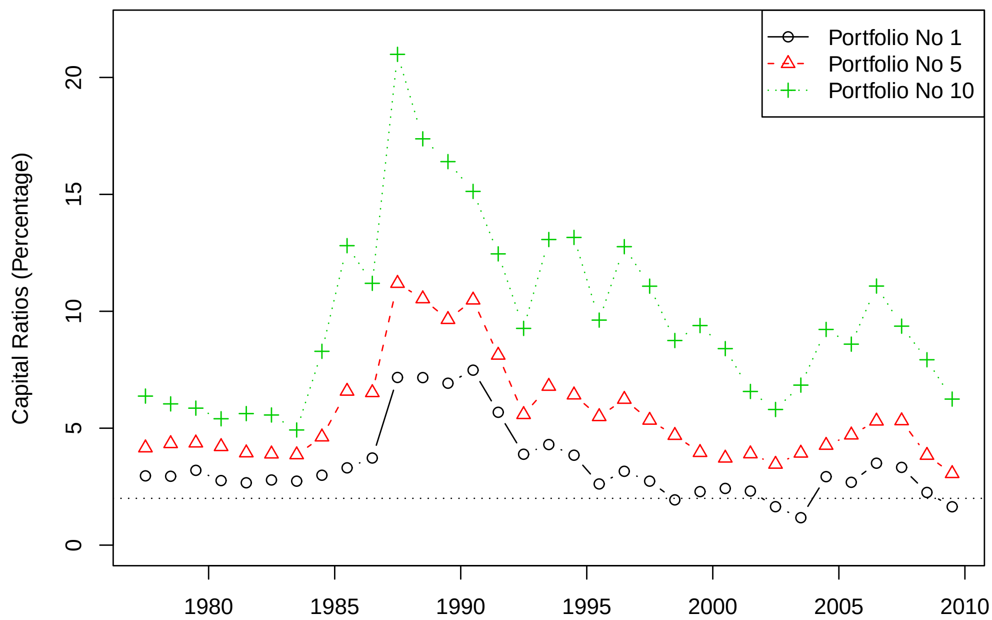


Figure 5.2: Cross-Sectional Variations in Capital Ratios over Years (1977-2009)

in the following sections, we are about to investigate their underlying driving forces by using listed Japanese commercial banks data from 1977–2009. In particular, by adapting the log-linearized present-value model, we would be able to decompose the variations in capital ratios into three components: the variations in expected future discount rates, expected future profitability and expected leverage ratios. This decomposition allows us to conduct the variance decomposition to show exactly how much the variations in expected future discount rates and future profitability have contributed to the variations in bank capital ratios.

5.3 Decomposing the Capital Ratios

5.3.1 Present-Value Model

The market value of a bank's stock is the expected discount present value of future cash flow:

$$M_t = \sum_{j=1}^{\infty} E_t(D_{t+j})/(1+r)^j, \tag{5.1}$$

where M_t is the value of market equity at time t, $E_t(D_{t+j})$ is the expected dividend in period $t+j$, and r is the average expected return. As emphasized by Campbell and Shiller (1988), the valuation model in Eq. (5.1) is a tautology that defines the average expected return r. Provided that earnings (Y), dividends (D) and book equity (B) satisfy the clean-surplus accounting relation, we would also have a dynamic identity as follows:

$$B_{t+1} - B_t = Y_{t+1} - D_{t+1}, \tag{5.2}$$

where Y_{t+1} is the equity earnings per share during period $t+1$, $B_{t+1} - B_t$ denotes the changes in book equity per share. Substituting Eq. (5.2) into Eq. (5.1), the above discounted present-value model then becomes:

$$M_t = \sum_{j=1}^{\infty} E_t(Y_{t+j} - \Delta B_{t+j})/(1+r)^j. \tag{5.3}$$

Dividing both sides of Eq. (5.3) by current book values of total assets per share at time t (A_t), we obtain:

$$\frac{M_t}{A_t} = \frac{\sum_{j=1}^{\infty} E_t(Y_{t+j} - \Delta B_{t+j})/(1+r)^j}{A_t}, \tag{5.4}$$

$E_t(Y_{t+j})$ is the expected earnings at time $t+j$, $E_t(\Delta B_{t+j})$ denotes the expected changes in book equity.

Eq. (5.4) provides an overall framework about how the three factors, expected profitability, average expected stock returns and expected growth in book equity, combine to explain the time-series and cross-sectional variations in capital ratios. It shows clearly that high capital ratios must mechanically come from either one or a combination of the three facts: higher expected future earnings relative to current total assets, lower future stock returns, or lower expected growth in book equity relative to current total assets.

However, this present-value model may not be useful for conducting quantitative analysis. We then derive an approximated log-linearized present-value model as our main framework to show quantitatively how much these factors contributed to the variations in bank capital ratios respectively.

5.3.2 Log-Linearized Present-Value Model

As suggested by and Fama and French (2006), the valuation model in Eq. (5.4) is also a tautology that defines the average expected return r given clean-surplus accounting. Similarly, we can yield a more convenient and operational approximated linearized present-value model to decompose the capital ratios by defining the log stock returns (r_t) and log accounting returns on equity (e_t) as follows.

$$r_t = \log(\frac{M_{t+1} + D_{t+1}}{M_t}) = \log(1 + \frac{\Delta M_{t+1} + D_{t+1}}{M_t}), \tag{5.5}$$

$$e_t = \log(1 + \frac{Y_{t+1}}{B_t}) = \log(1 + \frac{\Delta B_{t+1} + D_{t+1}}{B_t}), \tag{5.6}$$

After some algebra, we can rewrite the above two equations as follows:

$$r_t = \log(1 + \exp(m_{t+1} - d_{t+1})) - (m_t - d_t) + \Delta d_{t+1}, \tag{5.7}$$

$$e_t = \log(1 + \exp(b_{t+1} - d_{t+1})) - (b_t - d_t) + \Delta d_{t+1}, \tag{5.8}$$

Where m_t represents the log market values of equity of a bank, b_t is the log book values of equity of a bank, Δd_t is the log dividend growth rate. We then approximate both log stock returns and accounting returns on equity by first-order Taylor-expansion by choosing the same expansion point:

$$r_t \approx \alpha + \rho(m_{t+1} - d_{t+1}) - (m_t - d_t) + \Delta d_{t+1}, \tag{5.9}$$

$$e_t \approx \alpha + \rho(b_{t+1} - d_{t+1}) - (b_t - d_t) + \Delta d_{t+1}, \tag{5.10}$$

where ρ is a parameter. As long as banks pay any dividends, the discount parameter would satisfies $\rho < 1$. Since the choice of ρ is an empirical question, we follow Vuolteenaho (2002) and Cohen, Polk and Vuolteenaho (2003) to set ρ at 0.96.[4] By subtracting (5.9) from (5.10) and arranging terms, we can derive the one-period approximate model for a bank's capital ratio ($\theta_t \equiv \log(M_t/A_t)$ as follows:

$$\theta_t = e_{t+1} - r_{t+1} + (\phi_t - \rho\phi_{t+1}) + \rho\theta_{t+1}, \tag{5.11}$$

Where ϕ_t denotes the log leverage ratio $b_t - a_t$. We can iterate forward Eq. (5.11) to express the capital ratio as an discounted sum of future profitability, future stock returns, current and future linear combination of accounting leverage ratios, and future capital ratios.

$$\theta_t = \sum_{j=1}^{k} \rho^{j-1} e_{t+j} - \sum_{j=1}^{k} \rho^{j-1} r_{t+j} + \sum_{j=1}^{k} \rho^{j-1}(\phi_{t+j-1} - \rho\phi_{t+j}) + \rho^{k+1}(\theta_{t+k}). \tag{5.12}$$

Provided that the capital ratio is stationary and ρ is less than one, the last term of Eq. (5.12) would converge to zero as $k \to \infty$. We can also express the capital ratio as an infinite discounted sum of future profitability, future stock returns and current and future changes in accounting leverage ratio:

$$\theta_t = \sum_{j=1}^{\infty} \rho^{j-1} e_{t+j} - \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} + \sum_{j=1}^{\infty} \rho^{j-1}(\phi_{t+j-1} - \rho\phi_{t+j}). \tag{5.13}$$

Since it is an (approximated) identity, it holds ex post as well as ex ante. We could add E to express it as a present-value model as follows:

$$\theta_t = E_t \sum_{j=1}^{\infty} \rho^{j-1} e_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} + E_t \sum_{j=1}^{\infty} \rho^{j-1}(\phi_{t+j-1} - \rho\phi_{t+j}), \tag{5.14}$$

[4] We confirmed that all the following results would not change materially as we give small changes to ρ.

where the expectation operator E can refer to any information set that includes capital ratios, e.g. investor's information set. Therefore, the capital ratios reveals a slice of investor's information about expected returns, expected profitability and expected changes in leverage ratios. In other words, the variations in capital ratios must mechanically from either changes in expected returns, expected profitability, or expected leverage ratios.

By employing the approximated linearized present-value relation rather than the exact present-value relation in Eq. (5.4), we could use linear models to construct proxies for future expectations. The approximated log-linearized model then provides us the quantitative framework to examine the time-series and cross-sectional variance decomposition of bank capital ratios.

5.4 Time-Series Variance Decomposition

In this section, we explore the question about how much each factor has contributed to the time-series variations in bank capital ratios. First, we decompose the variance of capital ratios into the sum of the variance of expected future profitability, expected future stock returns, expected future leverage ratios, and the covariance terms between them, based on the log-linearized present-value model (5.14).

We postulate a simple first-order VAR representation of log accounting returns on equity, log stock returns, and log capital ratios, with log capital ratios as the only right-hand-side forecasting variable to focus on the forecasts based on capital ratios.

$$
\begin{aligned}
e_{t+1} &= \alpha_e + \beta_e \theta_t + \epsilon_t^e, \\
r_{t+1} &= \alpha_r + \beta_r \theta_t + \epsilon_t^r, \\
\theta_{t+1} &= \alpha_\theta + \beta_\theta \theta_t + \epsilon_t^\theta,
\end{aligned} \tag{5.15}
$$

Since the approximate identity applies to each year, it allows us to derive additional identities linking the regression coefficients and errors in the VAR system according to the log-linearized identity (5.11). We thus could drop one of the redundant equation in the VAR system to infer the regression coefficients, errors and data of any equation from the information of the other equations. Here, we chose to drop the equation about the term of leverage ratios as shown above.[5] All variables used in the corresponding time-series variance decomposition analysis are based on a per-share and valued-weighted basis.[6] The regression results are reported in Table (5.2).

Panel (A) reports the results for the case of all banks. The return forecasting coefficient is about -0.22, pretty significant both in the economic and statistical sense. The profitability forecasting coefficient is about 0.04, close to zero. The implied coefficient of leverage ratio is also very small, just about -0.03. The estimated coefficient of the capital ratio autocorrelation is above

[5]It could be justified by our motivation to unveil the relative importance of profitability and expected stock returns. Therefore, it may be useful to estimate them directly.

[6]We would use the valued-weighted quantities calculated from all banks as our benchmark, accompanying with results estimated from valued-weighted quantities for city banks and regional banks.

0.8 showing some strong persistence. The cases for city banks and regional banks present similar patterns with the all bank case.

On the right side of Table (5.2), we report standard deviations of the regression errors on the diagonal of the error terms matrix and correlation between errors on the off-diagonal. The stock returns have a large standard deviation about 30 percent, and the standard deviation of capital ratios is also quite large, close to that of stock returns. The variability of profitability and leverage ratios are limited. Capital ratio and return shocks are strongly positively correlated, while the correlation between capital ratio and profitability shocks is small.

We could then produce the decomposition of bank capital ratios in Eq. (5.14) based on the above simple VAR representation. This decomposition allows us to compute the variance and standard deviations of each components to answer quantitatively the question about how much the variations in capital ratios come from the variations in future expected stock returns and future profitability.

The variance decomposition results are reported at Table (5.3). Odd numbered rows reports the variance and standard deviations of each component, while even numbered row (in parenthesis) show the contribution of each component as a percentage of variance of capital ratios. It is evident that dynamic variations in capital ratios are dominated by the changes in expected stock returns. In either one of the three cases, almost all (about 90%) of the variations in capital ratios could be explained by changes in expected stock

Table 5.2: Time-Series Forecasting Regressions

	Coefficient Estimates			Error Terms			
	$\hat{\beta}$	SE	R^2	r	e	b	θ
Panel A: All Banks							
r	-0.219	0.100	0.094	0.302	0.410	0.100	0.966
e	0.046	0.028	0.051	0.410	0.089	-0.538	0.296
b	-0.035	0.035	—	0.410	0.089	0.081	0.296
θ	0.802	0.084	0.621	0.966	0.296	-0.013	0.278
Panel B: City Banks							
r	-0.269	0.135	0.119	0.370	0.311	0.197	0.961
e	0.079	0.041	0.106	0.311	0.115	-0.570	0.202
b	-0.065	0.048	—	0.197	-0.570	0.115	0.073
θ	0.747	0.122	0.555	0.961	0.202	0.073	0.338
Panel : Regional Banks							
r	-0.179	0.091	0.080	0.194	0.500	0.250	0.931
e	0.025	0.021	0.029	0.500	0.047	-0.083	0.330
b	-0.004	0.019	—	0.250	-0.083	0.059	-0.039
θ	0.834	0.079	0.702	0.931	0.330	-0.039	0.175

Note: This table reports the parameter estimates for the simple forecasting regressions. Each row represents an forecasting regression on the capital ratio shown at Eq. (5.15) in annual data from 1977 to 2009. The relevant statistics of leverage ratios are inferred from the other forecasting regressions. The discount coefficient ρ is set to 0.96. In parenthesis are GMM-corrected heteroskedasticity-consistent standard errors. The diagonal of the error terms matrix are standard deviations of the regression errors, while the off-diagonal are correlation between errors.

returns, while the contributions from the other two factors are quite limited compared to expected stock returns. Although the result shows that time-series variations in capital ratios are mostly driven by expected stock returns, this does not necessarily imply that the changes in expected profitability are not important. Note that the expected stock returns and expected profitability are correlated; this is not a decomposition into orthogonal components. It is possible that relatively small changes in expected profitability could cause large variations in expected stock returns.

In addition, we could also decompose the variance of capital ratios into its covariance with future profitability, future stock returns, and future changes in leverage ratios.[7] In particular, to derive the time-series variance decomposition, we multiply both sides of (5.12) by θ_t and take expectations:

$$\begin{aligned} var(\theta_t) = &\sum_{j=1}^{k} \rho^{j-1} cov(e_{t+j}, \theta_t) - \sum_{j=1}^{k} \rho^{j-1} cov(r_{t+j}, \theta_t) \\ &+ \sum_{j=1}^{k} \rho^{j-1} cov(\omega_{t+j}, \theta_t) + \rho^{k+1} cov(\theta_{t+k}, \theta_t), \end{aligned} \tag{5.16}$$

$$\begin{aligned} 1 = &\frac{\sum_{j=1}^{k} \rho^{j-1} cov(e_{t+j}, \theta_t)}{var(\theta_t)} - \frac{\sum_{j=1}^{k} \rho^{j-1} cov(r_{t+j}, \theta_t)}{var(\theta_t)} \\ &+ \frac{\sum_{j=1}^{k} \rho^{j-1} cov(\omega_{t+j}, \theta_t)}{var(\theta_t)} + \frac{\rho^{k+1} cov(\theta_{t+k}, \theta_t)}{var(\theta_t)}, \end{aligned} \tag{5.17}$$

where ω_{t+j} is a short-hand for $\phi_{t+j-1} - \rho\phi_{t+j}$. The four terms on the right-hand-side of Eq. (5.17) represent the fraction of variance in the capital

[7] It is similar to Cochrane (1992) who studies a variance decomposition for price-dividend ratios.

Table 5.3: Time-Series Variance Decomposition

	Profitability	Leverage	Returns
Panel A: All Banks			
Variance	0.008	0.005	0.178
	(0.040)	(0.023)	(0.905)
Standard deviation	0.089	0.068	0.422
	(0.201)	(0.153)	(0.952)
Panel B: City Banks			
Variance	0.020	0.014	0.231
	(0.077)	(0.053)	(0.907)
Standard deviation	0.140	0.116	0.481
	(0.278)	(0.230)	(0.952)
Panel C: Regional Banks			
Variance	0.002	0.000	0.083
	(0.016)	(0.000)	(0.803)
Standard deviation	0.040	0.007	0.288
	(0.126)	(0.022)	(0.896)

Note: The variance of capital ratios is decomposed into the sum of the variance of expected future profitability, expected future stock returns, expected future leverage ratios, and the covariance terms between them. The covariance terms are not reported here. The estimation is through the simple forecasting regressions reported in Table (5.2). The discount coefficient ρ is set to 0.96. In parenthesis are the fraction of variance (standard deviation) in capital ratios explained by the corresponding terms.

ratio attributable to the four sources of variations. Moreover, each term corresponds to a simple forecasting regression coefficient. Similarly, working with (5.13) by taking limit $k \to \infty$, we could drop the last term of Eq. (5.16) and Eq. (5.17) to yield:

$$1 = \frac{\sum_{j=1}^{\infty} \rho^{j-1} cov(e_{t+j}, \theta_t)}{var(\theta_t)} - \frac{\sum_{j=1}^{\infty} \rho^{j-1} cov(r_{t+j}, \theta_t)}{var(\theta_t)} + \frac{\sum_{j=1}^{\infty} \rho^{j-1} cov(\omega_{t+j}, \theta_t)}{var(\theta_t)}. \tag{5.18}$$

We employ the following three long-horizon forecasting regressions to measure the fraction of information contained in a bank's capital ratio about the four contributing covariance components in Eq. (5.17).

$$\begin{aligned}
&\sum_{j=1}^{k} \rho^{j-1} e_{t+j} = \alpha^{(e,k)} + \beta^{(e,k)} \cdot \theta_t + \epsilon_t^{(e,k)}, \\
&\sum_{j=1}^{k} \rho^{j-1} r_{t+j} = \alpha^{(r,k)} + \beta^{(r,k)} \cdot \theta_t + \epsilon_t^{(r,k)}, \\
&\rho^{k+1} \theta_{t+k} = \alpha^{(\theta,k)} + \beta^{(\theta,k)} \cdot \theta_t + \epsilon_t^{(\theta,k)}.
\end{aligned} \tag{5.19}$$

The regression results are reported at Table (5.4). The variance of capital ratios is decomposed into its covariance with expected future profitability, expected future stock returns, expected future leverage ratios, and future capital ratios. The first column shows the horizon k. The remaining columns represent the fraction of information that could be attributed to k-period profitability forecasts, k-period return forecasts, k-period leverage ratio forecasts, and k-period forecasts of future capital ratios respectively. The decomposition is estimated from the 1977 to 2009 value-weighted sample for all banks. At the one-year horizon, the largest variance component of capital ratios could be attributed to the covariance with next year's capital ratio (about 77 percent), which also contains the information in stock returns, profitability, and leverage ratios beyond the one-year horizon. The second is about 22 percent for stock returns. At the 20-year horizon, the variations in capital ratios are most driven by the expected stock returns, consistent with our earlier results. Since our direct long-horizon regressions use overlapping dependent variables, the regression errors are likely to be autocorrelated. We thus report the Newey-West standard error in parenthesis in order to account for the possible serial correlation of errors.

Figure (5.4) graphs the decomposition of time-series variance of bank capital ratios as a function of the horizon k. The top panel is the long-run coefficients implied by the simple VAR, while the bottom panel is the direct long-horizon estimates of the weighted long-horizon returns on capital ratios. Circles are log stock returns; triangles are log accounting returns on equity; cross-marks are implied leverage ratios; asterisks are future capital ratios. We could see that in both cases, the fraction of capital ratio variations explained by stock return forecasts increases quickly over horizons, while the fraction explained by future capital ratios declines rapidly and convergent to almost zero. The leverage ratios explain a very tiny fraction of time-series variations in capital ratios and convergent almost to zero as well. The decline in direct estimates of profitability forecasts means that long-run profitability moves in the wrong direction being expected. Although the estimates implied by the

Table 5.4: Time-Series Variance Decomposition by Long-Horizon Forecasting Regressions

k	Profitability	Returns	Leverage	Capital Ratios
1	0.0464	-0.2193	0.0352	0.7695
	(0.0351)	(0.1019)	(0.0349)	(0.0758)
5	-0.1508	-1.1176	0.0283	0.0615
	(0.2067)	(0.2352)	(0.1071)	(0.1520)
10	-0.6793	-1.9086	-0.0675	-0.2968
	(0.2009)	(0.2407)	(0.0955)	(0.1340)
15	-0.7861	-1.8259	-0.2221	-0.2619
	(0.0871)	(0.0950)	(0.0230)	(0.0404)
20	-0.4946	-1.4113	-0.0832	0.0000
	(0.0360)	(0.0640)	(0.0268)	(0.0335)

Note: This table reports the long-horizon forecasting regression coefficients. The variance of capital ratios is decomposed into its covariance with expected future profitability, expected future stock returns, expected future leverage ratios, and future capital ratios. The first column shows the horizon k. The remaining columns represent the fraction of information that could be attributed to k-period profitability forecasts, k-period return forecasts, k-period leverage ratio forecasts, and k-period forecasts of future capital ratios respectively. The decomposition is estimated from the 1977 to 2009 value-weighted sample for all banks. The results from both the city banks and regional banks, which are not reported here, do not change materially. The discount coefficient ρ is set to 0.96. In parenthesis are Newey-West heteroskedasticity-autocorrelation-consistent standard errors.

simple VAR give the right sign, the magnitudes are small at all horizons. In sum, all the empirical results here suggest that the expected stock returns is the dominant driving force in the time-series variations in bank capital ratios.

5.5 Cross-Sectional Variance Decomposition

In this section, we explore a related question about how much each factor has contributed to the cross-sectional variations in bank capital ratios. We create 10 value-weighted portfolios by sorting banks on capital ratios at the end of June in each year. We calculate the capital ratios as market equity at the end of June of year t, divided by the total assets for the last fiscal year ending in March. We then record the corresponding value-weighted log stock returns and log profitability for each portfolio over the subsequent year.

To derive the cross-sectional variance decomposition, we multiply both sides of (5.12) by $\tilde{\theta}_t$ and take unconditional expectations:

$$\begin{aligned} var(\tilde{\theta}_t) = & \sum_{j=1}^{k} \rho^{j-1} cov(\tilde{e}_{t+j}, \tilde{\theta}_t) - \sum_{j=1}^{k} \rho^{j-1} cov(\tilde{r}_{t+j}, \tilde{\theta}_t) \\ & + \sum_{j=1}^{k} \rho^{j-1} cov(\tilde{\omega}_{t+j}, \tilde{\theta}_t)) + \rho^{k+1} cov(\theta_{t+j}, \tilde{\theta}_{k+1})), \end{aligned} \tag{5.20}$$

where tilde denotes the corresponding variable cross-sectionally demeaned. Thus, $var(\tilde{\theta}_t)$ is the average squared cross-sectionally demeaned capital ratio, representing the cross-sectional dispersion in capital ratios. Dividing both

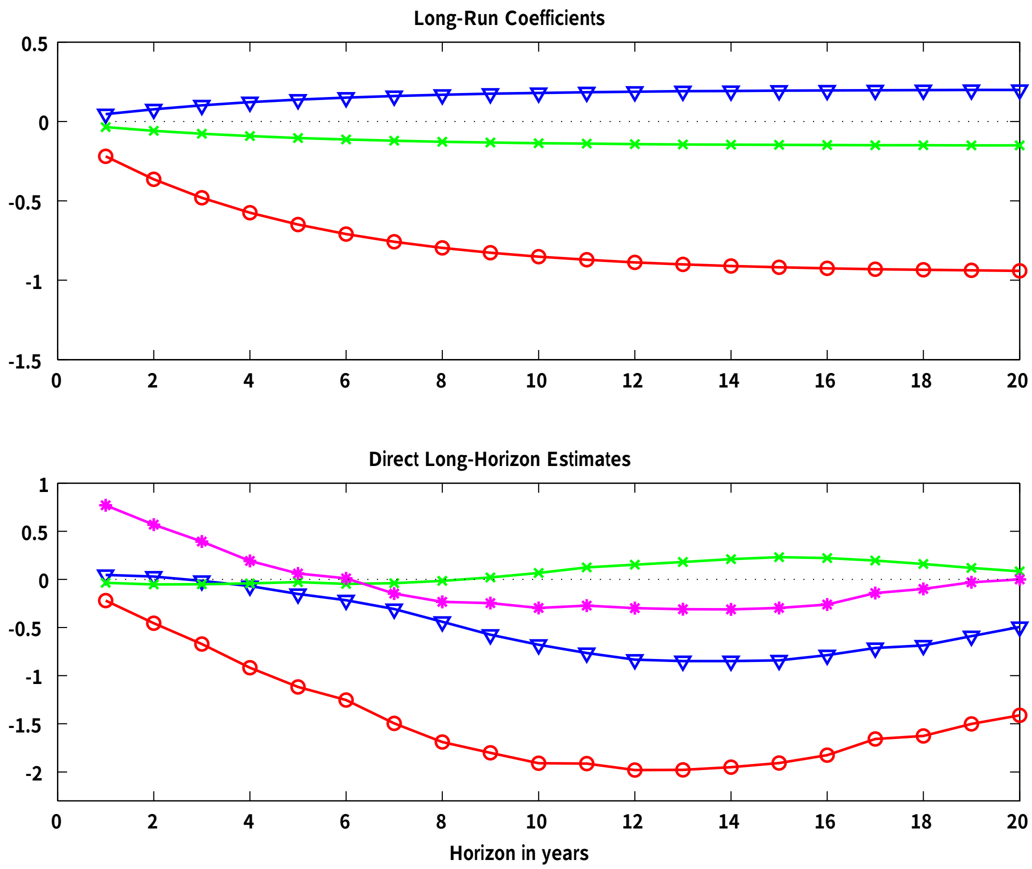


Figure 5.3: Decomposition of the Time-Series Variance of Bank Capital Ratios

Note: Long-horizon regression forecasts of discounted log accounting returns on equity, log stock returns and log capital ratios on capital ratios, as a function of the horizon k. The top panel is the long-run coefficients implied by the simple VAR, for example $\sum_{j=1}^{k} \rho^{j-1}\beta_{\theta}^{j-1}\beta_e$, while the bottom panel is the direct long-horizon estimates of the weighted long-horizon returns on capital ratios. Circles are log stock returns; triangles are log accounting returns on equity; cross-marks are implied leverage ratios; asterisks are future capital ratios.

sides by $var(\tilde{\theta}_t)$, we can derive Eq. (5.21) as follows:

$$\begin{aligned}1 =& \frac{\sum_{j=1}^{k} \rho^{j-1} cov(\tilde{e}_{t+j}, \tilde{\theta}_t)}{var(\tilde{\theta}_t)} - \frac{\sum_{j=1}^{k} \rho^{j-1} cov(\tilde{r}_{t+j}, \tilde{\theta}_t)}{var(\tilde{\theta}_t)} \\ &+ \frac{\sum_{j=1}^{k} \rho^{j-1} cov(\tilde{\omega}_{t+j}, \tilde{\theta}_t))}{var(\tilde{\theta}_t)} + \frac{\rho^{k+1} cov(\theta_{t+j}, \tilde{\theta}_{k+1}))}{var(\tilde{\theta}_t)},\end{aligned} \tag{5.21}$$

where the four terms on the right-hand-side of Eq. (5.21) represent the fraction of cross-sectional variance in the capital ratio attributable to the four sources of variations. Moreover, each term corresponds to a simple forecasting regression coefficient. Similarly, working with (5.13) by taking limit $k \to \infty$, we yield:

$$1 = \frac{\sum_{j=1}^{\infty} \rho^{j-1} cov(\tilde{e}_{t+j}, \tilde{\theta}_t)}{var(\tilde{\theta}_t)} - \frac{\sum_{j=1}^{\infty} \rho^{j-1} cov(\tilde{r}_{t+j}, \tilde{\theta}_t)}{var(\tilde{\theta}_t)} + \frac{\sum_{j=1}^{\infty} \rho^{j-1} cov(\tilde{\omega}_{t+j}, \tilde{\theta}_t))}{var(\tilde{\theta}_t)}. \tag{5.22}$$

We then employ the following three long-horizon forecasting regressions to measure the fraction of information in bank capital ratios about the bank's future:

$$\begin{aligned}&\sum_{j=1}^{k} \rho^{j-1} \tilde{e}_{i,t+j} = \alpha^{(\tilde{e},k)} + \beta^{(\tilde{e},k)} \cdot \tilde{\theta}_{i,t} + \epsilon_{i,t}^{(\tilde{e},k)}, \\ &\sum_{j=1}^{k} \rho^{j-1} \tilde{r}_{i,t+j} = \alpha^{(\tilde{r},k)} + \beta^{(\tilde{r},k)} \cdot \tilde{\theta}_{i,t} + \epsilon_{i,t}^{(\tilde{r},k)}, \\ &\rho^{k+1} \tilde{\theta}_{i,t+k} = \alpha^{(\tilde{\theta},k)} + \beta^{(\tilde{\theta},k)} \cdot \tilde{\theta}_{i,t} + \epsilon_{i,t}^{(\tilde{\theta},k)},\end{aligned} \tag{5.23}$$

where the subscripts refer to portfolio (i) and year (t). We estimate the regression coefficients with pooled OLS by using the 10 value-weighted portfolios from the year of 1977 through 2009. Since all data are cross-sectionally demeaned, we are only using cross-sectional information.[8]

The regression results are reported at Table (5.5). The first column shows the horizon k. The remaining columns represent the fraction of information that could be attributed to the k-period discounted profitability forecasts, the k-period discounted stock return forecasts, the implied k-period discounted leverage ratio forecasts, and the k-period-in-the-future forecasts of log capital ratios respectively. The decomposition is estimated from the 1977 to 2009 sample of all banks. Each year consists 10 portfolios formed by sorting banks on capital ratios. At the one-year horizon, the cross-sectional variations in capital ratios are split into its covariance with expected future one-year profitability, future one-year ahead stock returns, one-year ahead leverage ratios, and one-year ahead capital ratios. The largest variance component of capital ratios could be attributed to the covariance with next year's capital ratio (about 93 percent). Of course, the next year's capital ratio also captures the information in stock returns, profitability, and leverage ratios beyond the one-year horizon. The expected stock returns and expected profitability have also contributed to the variations significantly at the one-year horizon (about 12 percent for each component). The effect of expected changes in leverage ratios are not only very small in economic sense, but also insignificant in

[8]It is equivalent to a panel regression with time dummies. It is also similar to Fama-MacBeth regressions (Fama and MacBeth 1973) . While our regressions give more weights to years with more spread of independent variables, the FM regression pays equal attention to each year. The FM regressions would also produce a very similar results.

the statistical sense. The remaining rows look further into 5,10,15,20 years horizon. At the 20-year horizon, the variations in capital ratios are most driven by the expected stock returns and expected profitability.

Numbers in parenthesis of Table (5.5) report the robust standard errors for the variance decomposition that account for cross-sectional and serial correlation of errors. The ordinary OLS standard errors are likely to be significantly biased in the panel data set, since regression errors could be correlated across years for a given portfolio, or correlated across portfolios for a given year (e.g. Petersen 2009). First, when a bank's stock return is unusually high, another bank's return is also like to be high this year. The error terms therefore may be cross-sectionally correlated for a given year. Second, since our direct long-horizon regressions use overlapping dependent variables, the regression errors are also likely to be autocorrelated. We thus use the robust standard errors clustered by bank portfolio and year to account for cross-sectional and serial correlation of errors.

Since longer-horizon prediction regressions would reduce the number of independent observations in our sample, the standard errors would be expected to grow with the prediction horizon. It is exactly what we find in the data shown in Table (5.5). Although the standard errors grow with the prediction horizon, the coefficient estimates of expected stock returns and expected profitability grow even faster than the speed of standard errors. As a result, their statistical significance increases with the horizon as well. On the other hand, we cannot even reject the hypothesis at conventional levels

Table 5.5: Cross-Sectional Variance Decomposition by Long-Horizon Forecasting Regressions

k	Profitability	Returns	Leverage	Capital Ratios
1	0.122	-0.112	0.052	0.938
	(0.043)	(0.032)	(0.060)	(0.015)
5	0.525	-0.472)	0.139	0.808
	(0.176)	(0.099)	(0.250)	(0.034)
10	0.853	-0.827	0.259	0.715
	(0.276)	(0.191)	(0.446)	(0.030)
15	1.055	-1.166	0.435	0.677
	(0.302)	(0.336)	(0.612)	(0.043)
20	1.258	-1.557	(0.738	0.561
	(0.311)	(0.376)	(0.641)	(0.051)

Note: This table reports the cross-sectional variance decomposition of bank capital ratios. The variance of capital ratios is decomposed into its covariance with expected future profitability, expected future stock returns, expected future leverage ratios, and future capital ratios. The first column shows the horizon k. The remaining columns represent the fraction of information that could be attributed to the k-period discounted profitability forecasts, the k-period discounted stock return forecasts, the implied k-period discounted leverage ratio forecasts, and the k-period-in-the-future forecasts of log capital ratios respectively. The decomposition is estimated from the 1977 to 2009 sample of all banks. Each year consists 10 portfolios formed by sorting banks on capital ratios. The discount coefficient ρ is set to 0.96. The point estimates are computed with pooled OLS by using the cross-sectionally demeaned data. In parenthesis are cluster robust standard errors that account for cross-sectional and serial correlation of errors.

for all horizons that no variance in capital ratios is due to expected leverage ratios. This fact also suggests that the cross-sectional variations in capital ratios are mainly driven by expected profitability and stock returns.

Figure (5.4) graphs the decomposition of cross-sectional variance of bank capital ratios as a function of the horizon k. Circles are log stock returns; triangles are log accounting returns on equity; cross-marks are implied leverage ratios; asterisks are future capital ratios. The fraction of variations in capital ratios explained by stock return forecasts and profitability forecasts increases quickly and almost in the same rate over horizons. The relative importance of leverage ratios also increases over horizons. The fraction explained by future capital ratios, on the other hand, declines gradually over horizons.

In sum, our results about the cross-sectional variance decomposition suggest that banks with higher capital ratios are in a large part due to the their higher expected profitability and lower expected returns on their stocks. In contrast to the time-series case, the expected future profitability has played an almost equally important role as the expected stock returns in the cross-sectional variations in bank capital ratios. Moreover, the expected leverage ratios and expected persistence of capital ratios may have also contributed to the cross-sectional variations in capital ratios, although they are not as important as the expected stock returns and expected profitability.

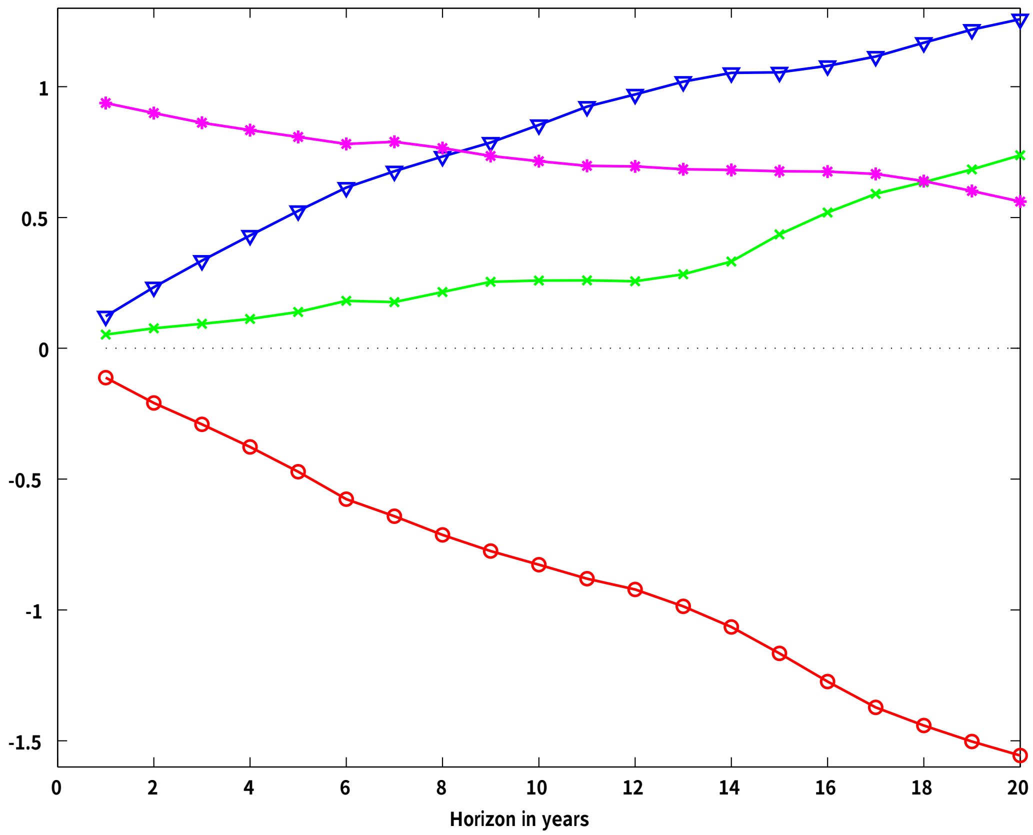


Figure 5.4: Decomposition of the Cross-Sectional Variance of Bank Capital Ratios

Note: This figure shows the decomposition of cross-sectional variance of bank capital ratios estimated from the 1977 to 2009 sample of all banks, as a function of the horizon k. Each year consists 10 portfolios formed by sorting banks on capital ratios. In particular, this figures shows the direct coefficient estimates of the k-period discounted log stock returns, the k-period discounted log profitability, the implied k-period discounted log leverage ratios, and k-period-in-the-future discounted log future capital ratios on the log capital ratios by using the cross-sectionally demeaned data. Circles are log stock returns; triangles are log accounting returns on equity; cross-marks are implied leverage ratios; asterisks are future capital ratios.

5.6 Conclusion

In this paper, we have documented the time-series and cross-sectional variations in bank capital ratios and investigates their underlying driving forces by using listed Japanese commercial banks data from 1977 to 2009. In particular, by adapting the log-linearized present-value model we would be able to decompose the variations in capital ratios into three components: the variations in expected future discount rates, expected future profitability and expected leverage ratios. This decomposition allows us to conduct the variance decomposition to show exactly how much the variations in expected future discount rates and future profitability have contributed to the variations in bank capital ratios respectively. Our empirical results have showed that changes in expected future discount rates dominate in the time-series variation of bank capital ratios, while the expected future profitability has played an almost equally important role as the expected discount rates in the cross-sectional variations.

Chapter 6

Volatility Spillover between Chinese and Major International Stock Markets

6.1 Introduction

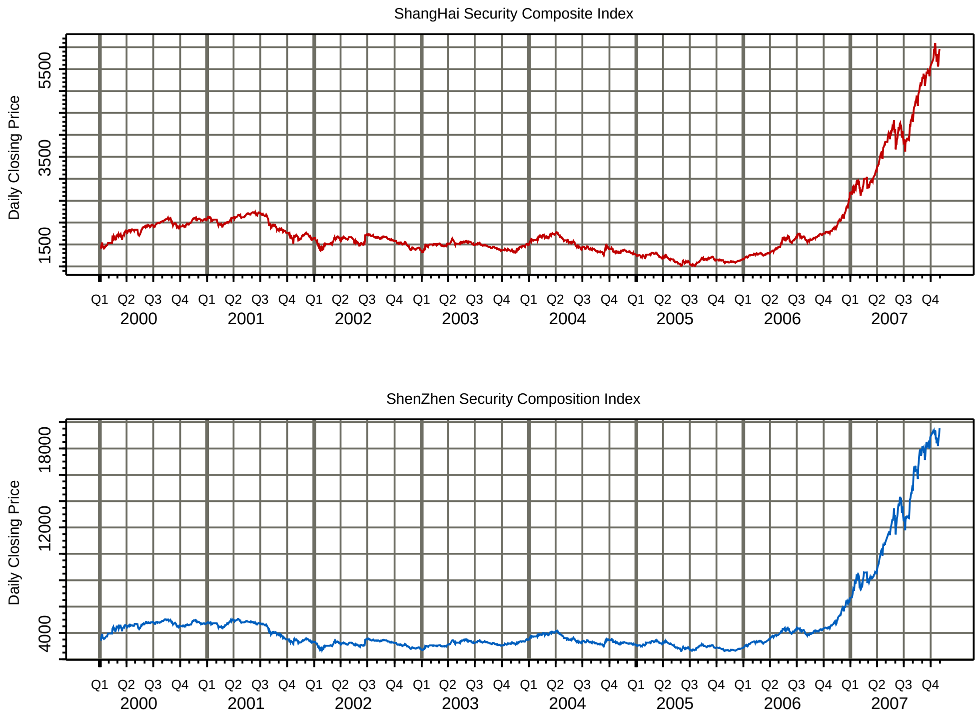
International markets have become more open and liberalized over the past two decades, leading to a common perception that global capital markets have become more integrated. As one of the typical emerging markets, China has also been undergoing financial liberalization and reform in recent years. Although it has been still holding the balance of world in the international trade and absorbing direct investment area for a long time, its domestic stock market has attracted more attention in the last two years. From the end of

2005 till the midyear of 2007, Shanghai Securities Composite Index and Shenzhen Securities Composition Index, two major indices of China, had gained about 500% and 600% leap respectively.It raised concerns about the possible bubbles in the stock market in China. Since it would be extremely difficult to answer the question about whether it is a growth or bubble directly, we would like to address it by providing some relatively indirect evidence instead.[1]

One can also see some striking phenomena come forth in the surging era of the China's stock market. For example, August, 2007, during which the exposure of the sub-prime crisis pushed the panic button of the global financial markets and all the major stock markets experienced dramatic shrinkage, nevertheless, China's stock markets kept the rocketing path. On the contrary, when the Shanghai market encountered a 9%fall in the end of the February, 2007, all the major markets declined in the following trading day. Of course, examples by themselves can never be convincing, since one can assert that these phenomena were sheer coincidences that the plunge of stock prices occurred in China at the same time as the tumble of the developed world. However, there has been little research about that relationship.

[1]The word "bubble" seems to be used to mean distinct things across different situations. Some use the word "bubble" to mean any large appreciation in the stock market. Some use the word "bubble" to mean a violation of the transversality condition in which stock prices would grow so fast even there are no dividends at all. This case are usually called "rational bubble", which is not present in an equilibrium of infinite lived agents but could be existing at the overlapping generations models. Here, we use the word "bubble" to mean large variations in stock prices caused by changes in expected stock returns but they are considered to be disconnected with the real economy.

Figure 6.1: The Movement of China's A-shares Markets



Source: Yahoo! Finance

There have been a great many researching efforts with respect to the volatility linkage between the stock markets. Benefiting from the advance of the modern econometrics techniques, economists now hold more consensus in this field. Most research pointed out that the major security markets, especially the U.S. market, hold a significant impact to each other[2]. However, the evidence from the existing literature about the relationship between Chinese stock markets and international stock markets is somewhat mixed. The results seem to depend on the choice of time period and statistical methods[3].

Our approach is empirical that we do not specify a theoretical model but allowing the data to provide answer to the questions above. We employ the causality-in-variance approach to investigate the relationship between Chinese stock market and major international stock markets by using the daily data in recent two years. Causality-in-variance has its own special interest especially important in the field of finance and macroeconomic, as it is directly related to volatility spillover across asset markets. Existing literature have shown that volatility spillover effect among financial markets would provide implications for information transmission mechanisms. Ross (1989)) have shown that the volatility of return is directly related to the rate of information flow to the market. Engle, Ito and Lin (1990), on the other

[2]e.g. Arshanapalli and Doukas (1993) Harvey (1991), Kasa (1992) and Chan, et al. (1997). Ghosh (1999) Tuluca and Zwick (2001) and Lewis (2006)

[3]e.g. Bailey (1994), Hu, Chen, Fok and Huang (1997), Groenewold, Tang and Wu (2004), Laurence, Cai and Qian (1997), Huang, Yang and Hu (2000), Hong, Cheng, Liu and Wang (2004) and Ding, Su and Du (2007)

hand, have shown that volatility spillovers from one market to the other could be attributed to the time by which markets need to evaluate and interpret the new information or policy action. Those findings suggest that the volatility of return could provide significant implications for the information transmission mechanism across different markets. Therefore , we could expect that data on the volatility of returns could provide us the information mechanism between Chinese stock market and international major markets.

Our study contributes to the literature mainly in two aspects. First, we examine the mode of information transmission between the recent surging Chinese stock market and major international markets by using the causality-in-variance approach. Second, we identify the distinct information transmission patterns with international markets showed by different stock market indices, i.e. A-shares, B-shares and H-shares, which are all backed by Chinese companies. The rest of the chapter is organized as follows: In the next section, we outline our empirical methodology. In section 3, we describe the data. Section 4 reports our empirical results and followed by a short concluding remark.

6.2 Methodology

We briefly review the concept of causality-in-variance first. Then, we introduce two approaches (e.g. Cheung and Ng, 1996; Hafner and Herwartz, 2004) used in this chapter to test the causality-in-variance, including a short discussion about their advantages and disadvantages.

Suppose we have two stationary and ergodic time series Y_{it} $(i = 1, 2)$. Let I_{it} $(i = 1, 2)$ be the information set of series Y_{it} respectively and $I_t = (I_{1t}, I_{2t})$. Y_{2t} is said to Granger-cause Y_{1t} in mean with respect to I_{t-1} if:

$$E\{Y_{1t} \mid I_{1t-1}\} \neq E\{Y_{1t} \mid I_{t-1}\} \equiv \mu_{1t}. \tag{6.1}$$

It is then a natural extension to define the causality-in-variance similarly. In particular, Y_{2t} is said to Granger-cause Y_{1t} in variance with respect to I_{t-1} if[4]:

$$E\{(Y_{1t} - \mu_{1t})^2 | I_{1t-1}\} \neq E\{(Y_{1t} - \mu_{1t})^2 | I_{t-1}\}. \tag{6.2}$$

Cheung and Ng (1996) have proposed a two-stage procedure to test causality relationship in variance and identify patterns of causation, based on the cross-correlation function (CCF) of squared-standardized residuals. In the first stage, we need to estimate the univariate time-series models by allowing for changing means and variances. And then we would compute the sample CCF of the squares of resulting standardized residuals in the following second stage. The CCF approach is not only easy to conduct without involving simultaneous modeling of both the first and second moment inter- and intra-series dynamics, but could also identify the pattern of causation at the

[4]Note that any causality in mean is filtered out in defining μ_{it} be to be the mean of y_{it} conditional on the complete "bivariate" information to ensure that the existence of causality in mean will not affect causality in variance.

specific lag in the second moment. However, as some econometricians (Hong, 2001; Hafner and Herwartz, 2004) have pointed out, the CCF approach may suffer from the selection of lags when it comes to the examination of long-run causal relationship. In other words, when a small lag is used, it may not be large enough to include the lags that may appear in the causation pattern. On the other hand, when a large lag is used, the CCF test may not be fully efficient, because it gives equal weighting to each of the sample cross-correlation at both of the recent and remote past lags as well as the fact of decreased degree of freedom.

Hafner and Herwartz (2004) then have proposed a convenient alternative to the above residual based test to examine the long-run causal relationship without considering the specific number of lags. Their methodology is based on the BEKK form of multivariate GARCH framework to construct a Wald test on causality in variance. This test is expected to be especially useful to deal with the time-series which may have a long distributed lag such that the cross-correlation at each lag is small but their joint effect is significant. They also reported that the Wald test has superior power relative to the CCF approach, and is quite robust to misspecification of the order of the BEKK model, based on the Monte Carlo simulation.

6.2.1 CCF Approach

Suppose two series $Y_{it}, i = 1, 2$ can be written as :

$$Y_{it} = \mu_{it} + \epsilon_{it}, \tag{6.3}$$
$$\epsilon_{it} = \nu_{it}(h_{it})^{1/2},$$

where μ_{it} represents the mean equation such as ARMA model; while h_{it} denotes the variance equation such as GARCH models. ν_{it} are two independent white noise processes with zero mean and unit variance. In particular, following previous studies we are using the following standard AR(k)-EGARCH(p,q) model.

$$\mu_t = \pi_0 + \sum_{i=1}^{k} \pi_i Y_{t-i}, \tag{6.4}$$
$$\log h_t = \omega + \sum_{i=1}^{p} \frac{\alpha_i|\epsilon_{t-i}| + \gamma_i \epsilon_{t-i}}{h_{t-i}^{1/2}} + \sum_{i=1}^{q} \beta_i \log h_{t-i}.v$$

Let U_t, V_t be the squared standardized innovations, and ρ_{uv} be the sample cross-correlation at lag k:

$$U_t = \frac{(Y_{1t} - \mu_{it})}{h_{1t}} = \nu_{1t}^2, \tag{6.5}$$
$$V_t = \frac{(Y_{2t} - \mu_{it})}{h_{2t}} = \nu_{2t}^2,$$
$$\rho_{uv} = c_{uv}(k)(c_{uu}(0)c_{vv}(0))^{-1/2}, \tag{6.6}$$

where the $c_{uv}(k)$ is the kth lag sample cross covariance given by

$$c_{uv}(k) = T^{-1} \sum (U - \bar{U})(V - \bar{V}) \qquad \text{k=0, } \pm 1, \pm 2, \ldots, \tag{6.7}$$

Cheung an Ng(1996) then suggest to test the H_0 of non-causality in variance at a specific lag using a statistic as follows:

$$\sqrt{T}\rho_{uv}(k) \xrightarrow{a} N(0,1). \tag{6.8}$$

6.2.2 Multivariate GARCH Approach

In the case of the simplest bivariate model $Y_t = (Y_{1t}, Y_{2t})$, which is used in our study, we suppose that VARMA(p,q) model is as follows:

$$Y_t = \pi + \sum_{i=1}^{p} \theta_i Y_{t-i} + \epsilon_t + \sum_{j=1}^{q} \phi_i \epsilon_{t-j} \tag{6.9}$$

and the conditional covariance matrix H has the following BEKK(1,1) formulation:

$$H_t = CC' + A\epsilon_{t-1}\epsilon_{t-1}' A' + BH_{t-1}B', \tag{6.10}$$

where C is a lower triangular matrix(2×2), A and B are unrestricted square matrices(2×2), ϵ_t is the error vector. The null hypothesis of non-causality in variance (from Y_2 to Y_1) could be tested by imposing the following zero restrictions on matrices A and B as follows:

$$A^{(12)} = 0, B^{(12)} = 0, \tag{6.11}$$

where the superscript (12) denotes the $(1,2)$ element of the corresponding matrix.

Hafner and Herwartz (2004) suggest that the question about whether or not the Y_2 series granger-caused Y_1 in variance amount to test the significance of $A^{(12)}$ and $B^{(12)}$. In particular, parameters in our model could be represented as a vector θ:

$$\theta = (vech(C)^{'}, vec(A)^{'}, vec(B)^{'}). \tag{6.12}$$

Hafner and Herwartz then further suggest that the null hypothesis of no causality in the BEKK(1,1) model can be written as the following form of eq (6.13):

$$H_0 : \qquad \mathcal{Q}\theta = 0, \tag{6.13}$$

where $\mathcal{Q} = (0,0,0,\tilde{\mathcal{Q}},\tilde{\mathcal{Q}})$, $\tilde{\mathcal{Q}} = (0,0,1,0)$. We denotes a consistent estimator of the true parameter vector θ by $\hat{\theta}$ and assume that its asymptotic distribution is as follows:

$$\hat{\theta} \sim N(\theta, \hat{\sum}_{\theta}). \tag{6.14}$$

We could define a Wald statistic under the null hypothesis to be asymptoticly Chi square distributed with the degree of freedom of one:

$$W = (\mathcal{Q}\hat{\theta})^{'}(\mathcal{Q}\hat{\sum}_{\theta}\mathcal{Q})^{-1}(\mathcal{Q}\hat{\theta}) \sim \chi^2_{(1)}. \tag{6.15}$$

6.3 Data

Following earlier work in this area, we choose the S&P 500 index, FTSE 100 index, Nikkei 225 index and the Hang Seng index as the representatives of major international markets. For the indicators of Chinese stock market, we would employ the A-shares of Shanghai Securities Composite index

(SSEC hereafter) and the B-shares[5] of Shanghai Securities Composite index (SSEC(B) hereafter), and the H-shares of Chinese enterprises index of Hong Kong[6] (HKCE hereafter). Since most corporations included in the B-shares and H-shares are also listed in the SSEC A-shares market as well, it is reasonable to assume that information reflected by the these three different stock indices should be consistent in general. Our sample covers the daily returns data from January, 2006 through October, 2007, during which China's stock markets experienced a rocketing era, as Figure (6.1) depicts. All the data are obtained from Yahoo! Finance.

Although some recent studies used the low frequency weekly or monthly data in the analysis (e.g. Ding et al. 2007), we consider that the daily data could capture the high frequency variability and the information within the modern financial market more sufficiently. It is simply because that the advancement of IT techniques and the deepened globalization have made the transmission of information between markets much more rapid over the last decade. We also believe that rather than a longer phrase sample, a relative

[5]The B-shares are companies incorporated in mainland China and are traded in the mainland B-share markets (Shanghai and Shenzhen). B-shares are quoted in foreign currencies. In the past, only foreigners were allowed to trade B-shares. Starting from March 2001, mainlanders can trade B-shares as well. However, they must trade with legal foreign currency accounts

[6]The H-shares are also Chinese companies incorporated in China under Chinese law. They are listed on the Hong Kong Stock Exchange and subject to its stringent listing and disclosure requirements. The shares are denominated in H.K. dollar and traded like any other shares listed on the Hong Kong Exchange.

shorter one could also avoid the potential break point bias.

The returns were calculated by using daily closing price based on the simple return formula: $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$, although log returns are typically used in the relating literature when dealing with the statistical analysis of stock returns, because of its nice additivity properties through time and the inclusion of the compounding effects. However, log returns may not be additive in a portfolio like stock index, in the sense that they are not a weighted average of the log returns on the individual stocks. On the other hand, the simple return on a portfolio of stocks is a weighted average of the simple returns on the individual stocks. Therefore, the simple return may be more appropriate for our purpose.

The daily data analysis also faces the trouble of inconsistent samples, since the non-trading days in each market are usually different. Some previous researches used the moving average to substitute the non-trading days. However, as Green (2003) pointed out, this method is no better than simply omitting the nonexistent data. Therefore, in analyzing every pair of the markets, when either one of the series comes through a non-trading day, we delete the corresponding data point of the other market on that day to make the sample pairs consistent.

Moreover, since Chinese stock markets and major international markets generally operate in different time zones, each index observed at the same time may not be synchronized. Thus, the time difference, which made the examination of information transmission among markets in the same day possible, should not be neglected either. In particular, when employing the CCF method to examine the variance-in-causality, any significant correlation of lag zero may be interpreted as evidence of Chinese stock markets causing the corresponding index of major international market in variance[7]. On the other hand, contemporaneous correlations are not concerned in the approach proposed by Hafner and Herwartz (2004).

6.4 Results

We employ the two-staged CCF approach proposed by Cheung and Ng (1996) to investigate the causality-in-variance relationship between Chinese stock markets and major international stock markets. In the first stage, we would do the estimation of univariate time-series using the AR(k)-EGARCH(p,q) model defined in equation (6.4). The number of lags was chosen through Akaike Information Criterion from the range of ($k = [1, 2, 3, 4, 5], p = [1, 2], q = [1, 2]$). The results are reported in Table (6.1). It is interesting to observe that the GARCH effect (β_1) in all models is highly significant with a coefficient close to one, indicating the characteristic of persistence in stock markets. It is also evident that both the $\mathcal{Q}(12)$ and $\mathcal{Q}^2(12)$ are not significant in the traditional significant levels. These results indicate that the selected models adequately describe both the mean and the variance.

In the second stage, we compute the resulting CCF of the squares of stan-

[7]Japan is the only exception.

dardized residuals. The CCF of these squared-standardized residuals could be used to test the null hypothesis of no causality-in-variance at a specific lag. Table (2) reports the results of eight market pairs, from which we could obtain two main findings.

First, we find surprisingly that the SSEC causes international markets in variance significantly, indicating volatility spillover effects from the SSEC to major international markets, while there appears no feedback in variance in the reverse direction. Our results provide some evidence of international financial integration of China's A-share market,although only domestic investors and few QFII are allowed to participate in its A share market. It may indicate that the limits to the extent to which the de jure capital account regulation could be enforced effectively. On the other hand, at the risk of overstatement, we may argue that China may be viewed as the confidence or one of the engines of world economy by international investors. Therefore, market participants in global markets are watching A-share market closely. These factors may help explain the evidence of causality relationship in spite of capital control.

Furthermore, patterns of the causality-in-variance deserve some comments, as the rhythm of the information transmission among these markets are quite the same way. We could find that all the market pairs are significantly connected in the same trading days, which may indicate the fact that market participants in global markets are watching out closely with each other, and also verifying the perception of much more robust financial globalization.

Table 6.1: Estimation Results of AR-EGARCH Model

	SSEC	SSEC(B)	HKCE	S&P500	Nikkei225	FTSE100	HangSeng
π_0	0.386**	0.369*	0.265**	0.045	-0.031	-0.006	0.095
	(0.089)	(0.096)	(0.076)	(0.038)	(0.056)	(0.040)	(0.053)
π_1	-0.096*	0.034	0.069	-0.016	-0.085	-0.043	0.017
	(0.047)	(0.055)	(0.056)	(0.059)		(0.055)	(0.064)
π_2				-0.044		-0.056	
				(0.053)		(0.053)	
π_3				0.039		0.069	
				(0.052)		(0.052)	
π_4				-0.031		-0.082	
				(0.053)		(0.054)	
π_5				-0.128**			
				(0.048)			
ω	-0.060**	-0.053*	-0.155**	-0.103*	-0.032	-0.134**	-0.113**
	(0.020)	(0.025)	(0.034)	(0.053)	(0.024)	(0.050)	(0.051)
α_1	0.102**	0.267**	0.292**	0.091**	0.042	0.150**	0.156*
	(0.031)	(0.058)	(0.054)	(0.057)	(0.031)	(0.058)	(0.066)
β_1	0.987**	0.927**	0.942**	0.951**	0.982**	0.959**	0.908**
	(0.006)	(0.014)	(0.022)	(0.019)	(0.009)	(0.016)	(0.033)
γ_1	0.832**	0.075	-0.078	-0.999	-1.000	-0.991**	-1.000
	(0.265)	(0.111)	(0.092)	(0.909)	(0.983)	(0.474)	(0.521)
$\mathcal{Q}(12)$	12.60	10.57	13.03	14.94	10.20	4.59	14.53
	[0.399]	[0.567]	[0.367]	[0.245]	[0.598]	[0.970]	[0.268]
$\mathcal{Q}^2(12)$	9.60	1.95	12.64	5.91	14.01	7.26	16.33
	[0.651]	[0.999]	[0.396]	[0.921]	[0.300]	[0.840]	[0.176]

Note: This table reports estimation results of the AR-EGARCH model for SSEC, SSCE(B), HKEC, and S&P500 stock indices. The sample period for all these daily series is from Jan 4th 2006 through Oct 30th 2007. The number of lags was chosen through Akaike Information Criterion. In particular, AR(5)-EGARCH(1,1) model and AR(4)-EGARCH(1,1) model are chosen for S&P50, FTSE100 respectively, while AR(1)-EGARCH(1,1) model is for remaining indice. $\mathcal{Q}(12)$ and $\mathcal{Q}^2(12)$ are the Ljung-Box statistics for the first twelve autocorrelations of standardized residuals and squared standardized residuals respectively. Numbers in round parentheses are asymptotic standard errors of the corresponding coefficients. Numbers in square parentheses are p values of Ljung-Box statistics. *,** denote significance at $5\%, 1\%$ level respectively.

Taking into account the time difference, contemporaneous correlations between the SSEC and major international markets may also be viewed as evidence of immediate causal effect from the former to the later. In addition, there also appears some lags in the pattern of causality-in-variance, with three trading day's lag for U.S market, and four trading day's lag for remaining international markets. This results seems to suggest that investors in international markets may need some time to evaluate the new information occurred in the SSEC; and also verify the leading role of the U.S. in the global markets as well.

Second, in contrast with the SSEC, both the B-shares and the H-shares indices are not only closely related with the SSEC, but also significantly influenced by the U.S. market, implicating that investors in different markets hold inconsistent judgment about Chinese corporations. We should notice that every unit of the A-shares, the B-shares and the H-shares stock of Chinese companies owns the same legal rights and reflects the same fundamental information. It is thus simply confusing with the inconsistent results that their responses to global markets are just diverging persistently and significantly. This fact inevitably means that there may exists some degree of distortions in one of these markets. It is well known that there are more international investors participating in the B-shares and Hong Kong markets. In addition, the latter one is also being considered much more matured and efficient than the Shanghai market. Therefore, it is reasonable to argue that the independently surging markets of mainland China may hold tremendous potential risks, as distorted markets have the potential to experience undesirable adjustments suddenly.

As a complement to the CCF approach, we also report results of the Multivariate GARCH approach proposed by Hafner & Herwartz (2004) to examine the long-run causal relationship without considering the specific number of lags. We first apply the VARMA(p,q)-BEKK(1,1) model to estimate each pair of series of our interest. The appropriate lag was chosen from the range of ($p = [0, 1, 2], q = [0, 1, 2]$) based on the Akaike Information Criterion. The results are reported in Table (6.3). A number of parameters are estimated significantly, especially for the coefficients of BEKK model. We then conduct the Wald test by imposing zero restrictions on the parametric model defined in equation (6.15). The result of Wald tests under the null of no causality-in-variance is reported at Table (6.4). It is evident that results of two approaches are quite consistent. The Result from the Wald type test developed by Hafner and Herwartz (2004) verifies the important findings of the CCF approach reported in Table (6.2) that volatility spillover effects are from the SSEC to major international indices, but not vice verse. Meanwhile, it also reveals the SSEC's strong impact on the B-shares and the H-shares in the long run. The main difference, when compared to CCF approach, is that the relationship between the U.S. market and the B-shares market is not as significant as in the CCF approach.

Table 6.2: Sample Cross-Correlations of Squared-Standardized Residuals

lag(k)	(SSEC, S&P500)	(SSEC, Nikkei225)	(SSEC, FTSE100)	(SSEC, HangSeng)	(HKCE, S&P500)	(SSEC(B), S&P500)	(HKCE, SSEC)	(SSEC(B), SSEC)
-5	-0.005	-0.023	-0.036	0.040	0.004	-0.019	-0.015	0.017
-4	0.030	0.144**	0.100*	0.109*	-0.009	-0.034	-0.012	-0.011
-3	0.103*	-0.071	0.006	-0.020	-0.003	0.005	-0.013	-0.045
-2	-0.032	-0.015	0.060	-0.066	0.024	-0.008	0.001	-0.013
-1	0.016	0.091	-0.008	0.050	-0.034	0.068	0.059	-0.025
0	0.131**	-0.036	0.164**	0.104*	0.128**	0.114*	0.336**	0.293**
1	-0.033	0.078	-0.015	-0.012	0.199**	-0.021	0.017	-0.014
2	-0.009	-0.088	-0.024	0.006	0.001	-0.008	-0.007	-0.010
3	-0.063	-0.041	-0.048	0.017	0.001	-0.058	-0.067	-0.034
4	0.020	-0.086	-0.029	-0.034	0.104*	0.114*	0.025	0.002
5	0.012	0.010	0.059	0.026	0.031	-0.016	0.030	-0.037

Note: The sample period for all these daily series is from Jan 4th 2006 through Oct 30th 2007. The lag (k) refers to the number of periods that the former lags behind the later, while the lead (given by a negative lag (k)) refers to the number of periods that the former leads the later. Sample cross-correlations of squared-standardized residuals are used in detecting causation in variance. * and ** indicate significance at the 5% and 1% level respectively.

Finally, we also conduct a robust test using Shenzhen Securities Composition index (SZSC hereafter), which is almost parallel to the SSEC market for a long time. The industry distribution and scales of companies listed in this two market, together with the governance and regulations are almost the same. Therefore, it is reasonable to assume the Shenzhen market as a good substitute of our SSEC sample to check the robustness of above findings. The results from the Hafner & Herwartz's approach by substituting with the SZSC index reported in Table (6.5) presents a total approval to the previous findings[8].

6.5 Conclusion

Our results provide evidence to show immediate causality effects in variance from SSEC to major international markets within the same trading day, while there appears no evidence to show feedback in variance from the later to the former. We also observed causality-in-variance effect from SSEC to major international markets with some lags, three trading day's lag for U.S market, and four trading day's lag for remaining international markets. It seems to suggest that investors in international markets may also need some time to evaluate the new information occurred in the SSEC to be reflected in stock prices of the global markets; and verify the leading role of the U.S. in the

[8]We omit the results of CCF approach, which is also consistent with our early results.

Table 6.3: Estimation Results of VARMA-BEKK(1,1) Model

	(SSEC, S&P500)	(HKCE, S&P500)	(SSEC(B), S&P500)	(SSEC, HKCE)	(SSEC, SSEC(B))
π_1	0.292**	0.307**	0.392**	0.305**	0.260**
π_2	0.064*	0.056*	0.056	0.292**	0.220*
ϕ_1		0.089+			
ϕ_2		-0.264**			
C_{11}	0.210**	0.367**	0.751**	0.296**	0.217**
C_{21}	-0.015	0.069	-0.013	0.389	0.357+
C_{22}	0.053	0.079	0.001	0.000	0.381**
A_{11}	0.241**	0.330**	0.337**	0.062	0.277**
A_{21}	-0.076**	-0.052*	-0.031*	-0.280**	-0.139*
A_{12}	0.033	0.387**	-0.068	0.289**	0.020
A_{22}	0.158**	0.183**	0.192**	0.383**	0.445**
B_{11}	0.969**	0.909**	0.907**	0.994**	0.957**
B_{21}	0.032**	0.026*	0.018**	0.110**	0.039
B_{12}	-0.094**	-0.101*	-0.024	-0.196**	-0.004
B_{22}	0.899**	0.956**	0.972**	0.848**	0.900**

Note: This table reports estimation results of the VARMA-BEKK(1,1) model for pairs of SSEC, SSEC(B), HKEC, and S&P500 stock indices. The sample period for all these daily series is from Jan 4th 2006 through Oct 30th 2007. The number of lags was chosen through Akaike Information Criterion. In particular, the VARMA(0,1)-BEKK(1,1) model is chosen for the pair of HKCE and S&P50, while the VARMA(0,0)-BEKK(1,1) model is for remaining pairs. *,** denote significance at $5\%, 1\%$ level respectively. $^{+}$ indicates significance at 10% level.

Table 6.4: Hafner & Herwartz's Test

	Wald Statistics	P Value
SSEC $\longrightarrow$ S&P500	12.535	0.000
S&P500 $\longrightarrow$ SSEC	0.442	0.506
HKCE $\longrightarrow$ S&P500	2.866	0.090
S&P500 $\longrightarrow$ HKCE	10.584	0.001
SSEC(B)$\longrightarrow$ S&P500	1.651	0.199
S&P500 $\longrightarrow$ SSEC(B)	0.421	0.516
HKCE $\longrightarrow$ SSEC	6.509	0.011
SSEC $\longrightarrow$ HKCE	24.508	0.000
SSEC(B) $\longrightarrow$ SSEC	0.348	0.555
SSEC $\longrightarrow$ SSEC(B)	5.480	0.019

Note: The sample period for all these daily series is from Jan 4th 2006 through Oct 30th 2007.

Table 6.5: Robustness Test

	Wald Statistics	P Value
SZSC $\longrightarrow$ S&P500	5.070	0.024
S&P500 $\longrightarrow$ SZSC	0.049	0.825
HKCE $\longrightarrow$ S&P500	2.866	0.090
S&P500 $\longrightarrow$ HKCE	10.584	0.001
SZSC(B) $\longrightarrow$ S&P500	1.463	0.227
S&P500 $\longrightarrow$ SZSC(B)	0.032	0.858
HKCE $\longrightarrow$ SZSC	6.893	0.009
SZSC $\longrightarrow$ HKCE	6.701	0.010
SZSC(B) $\longrightarrow$ SZSC	7.052	0.008
SZSC $\longrightarrow$ SZSC(B)	7.611	0.006

Note: The sample period for all these daily series is from Jan 4th 2006 through Oct 30th 2007.

global markets as well.

In contrast, the B-shares and H-shares indices of China's enterprises, in which more international investors participate, were not only affected by A-shares markets, but also significantly sensitive to the information from the U.S. market. The inconsistent results compared with the A-shares index seems to imply that there may be remarkable distortion in the information enclosure, underestimated risks, or investors with much less risk-aversion in the A-shares market of mainland China, allowing potential room for sudden adjustments. Therefore, the regulatory institution and investors in China should be more alert to the potential danger.

Chapter 7

Concluding Remarks

The first two essays of my thesis aim to provide insights within the framework of asset pricing theory on the economic forces driving dynamic changes in the Japanese stock market based on historical data. Asset pricing theory tries to relate the price or value of claims to entire future uncertain cash flow stream usually in the form of present-value statement. The centerpiece of modern asset pricing theory is that prices should equal expected cash flow discounted by stochastic discount factor. This present-value framework provides a powerful organizing principle for empirical researches to divide the underlying driving forces in financial markets mainly into two parts: one is the expected cash flow part, the other one is discounted part.

The first essay explores the implications of a dynamic accounting identity for the dynamics of equity returns in a present-value framework by using data of cash flow and market equity value of Japanese private non-financial corporations. In particular, we study the role of fluctuations in dividend yield and equity payout yield for predicting equity returns. Valuation ratios such as dividend yield and equity payout yield are central to forecasting because they reveal a slice of agent's expectation about expected future returns and expected future cash flow. Our results provide economically and statistically significant evidence about the predictability of equity returns for Japanese corporations, and show that dividend yield is a better predictor of equity returns than equity payout yield. Moreover, we show that while the dividends are not predictable either by dividend yield or equity payout yield, there are predictable components in equity payout. The predictable components could largely be attributed to other cash flow such as equity repurchase and issuance rather than dividends.

In addition, we decompose equity returns into changes in current cash flow, changes in expected future cash flow and changes in expected equity returns, and compute the variance of each component to show how much variation in Japanese corporation's equity returns are due to changes in expected equity returns and expected changes in cash flow. In contrast to previous studies about the Japanese equity returns, we find that changes in expected future cash flow play a very small part in the variation of equity returns. In other words, history tells us that the dramatic changes in the equity market over the last two years may have little to do with investor's gloomy prospect about future cash flow of Japanese corporations.

The second essay employs a similar methodology to explore forces driving the movement of the J-REIT market. The results indicate that the news about cash flow plays an almost equally important role in the movement of the J-REIT return as well as changes in expectation of excess returns. This result is a little different from the first essay, which focus on the equity returns of Japanese corporations. It may attributed to the different characteristics of underlying assets between J-REIT equity and Japanese corporation's equity. J-REITs are required to distribute 90 percent of their income, while in return they are exempt from corporate income taxation. Therefore, the news about the dividends could be viewed as almost equivalent to the news about the rental income of the underlying properties in the case of J-REIT. It is thus the news about the rental income of the underlying properties that drives the J-REIT market. It suggests that dividends of Japanese corporations may represent mainly permanent components of cash flow to present no predictability, while dividends of J-REITs are expected to consist much more transitory components of cash flow.

I also take the question further to examine whether or not the J-REIT market has fully incorporated those news immediately. My results show that the J-REIT market has assimilated market news fully within a month lag. The much quicker price adjustment of the J-REIT market seems to suggest that it helped improve the informational efficiency of the real estate market in Japan. On the other hand, it also suggests that Japan may need to promote the securitization of real estate assets further on the basis of efficient asset pricing.

In short, we would be able to provide insights on the proximate causes driving the dynamics of the Japanese stock market, by applying this empirical approach to financial markets. Our results shows that risk premia reflected in variation of discount rates, expected returns may be the key factor that matters most for the dynamics of stock returns. On the other hand, we still need economic models to help understand the fundamental economic reasons about the proximate causes driving stock prices. Our empirical approach is silent on why the expected returns changes so much, so never really provide an economic explanation of fundamental forces in stock markets. However, our empirical discoveries may help us postulate the channels and mechanisms through which we can (and should) explore (and elaborate) further to link changes in asset prices to the fundamental economic events. In other words, if we really want to have an economic understanding of stock markets, to provide a convincing economic explanation about why prices are what they are over time, to predict how changes in policy action or economic structure would affect stock markets, we may need to link the stock market to macroeconomic events by exploring the subtle economics of risk premia rather than mechanisms causing fluctuations in cash flow alone.

The following two essays focus on proposing a market-valued capital ratio as a measure of bank risks, and explore forces driving the time-series and cross-sectional variations of bank capital ratios. In the third essay, we propose a market-valued capital ratio as an indicator to gauge the riskiness of banks. In particular, we study the question about whether the market-valued capital ratio or the BIS capital ratio is better at identifying risky banks by looking at the relationship between different measures of capital ratios and average returns of bank stocks.

In this essay, we take the position to extract information from asset prices based on the the asset pricing theory. In doing so, we may acquire comprehensive and timely information guiding our actions to evolving problems. Market-based indicators are generally forward looking, and could incorporate the relevant information, both in the form of formal knowledge and informal knowledge, from a wide range of sources very quickly. They reflect the overall assessment from the market instead of a bank's assessment of itself on specific on-balance-sheet credit holding. They are also difficult to be manipulated by banks consistently. Moreover, the excess expected returns reflect both the quantity and price of risk. The quantity of risk would vary from bank to bank, while the price of risk is the same for all banks. Since a huge amount of researches report that the dynamics of share prices are affected significantly by changing risk prices, we would also like to exploit the information from the cross-sectional variations of stock returns to focus mainly on the quantity of risk rather than studying the dynamics of bank stock returns.

Asset pricing theory predicts that systematic difference in average returns are due to difference in risk, provided stocks are not mis-priced systematically and persistently. If higher capital ratios indicate lower riskiness, banks with higher capital ratios would earn lower average returns. By using Japanese listed bank's data from 1990 through 2008, my results show that market-valued capital ratios associate negatively with average returns, while the BIS capital ratio, widely used by bank regulators, is showed to be positively related with average returns. These facts imply that banks may be risky despite of reporting higher BIS capital ratios. On the other hand, the market-valued capital ratios seem to serve as an informative indicator to identify risky banks. In addition, we also show that market-valued capital ratios proxy for sensitivity to risk factors that capture common variation in returns; and low (high) market-valued capital ratio signals persistently poor (strong) profitability.

Rather than proposing a market-valued capital ratio as one all-encompassing measure, we are expecting that it could be one of a list of potentially useful indicators to guide regulator's actions to evolving problems. In addition, our analysis also suggests that regulatory structure may not be a substitute for market discipline, since regulators could obtain comprehensive and timely information by monitoring market-based indicators. Therefore, it makes sense for regulators to enhance market discipline rather than replacing it.

In the forth essay, we document the time-series and cross-sectional variations in bank capital ratios and investigates their underlying driving forces by using listed Japanese commercial banks data from 1977–2009. Bank capital ratios vary over time and across banks. Intuitively, both expected stock returns and expected future profitability could influence the determination of bank capital ratios. We add to the literature by providing an overall framework on how theses factors combine to explain the time-series and cross-sectional variations in capital ratios. While book values are inherently backward looking, capital ratios based on market values are generally forward looking. It is therefore important to capture this feature into our considerations in investigating the driving forces of variations in capital ratios.

In addition, although previous works point out that capital ratios could be affected by either profitability or stock returns, no existing research has ever provided quantitative assessment about the relative importance of these factors in the determination of bank capital ratios. We aim to fill the gap by identifying quantitatively the relative importance of these factors in determining both the time-series and cross-sectional variations of bank capital ratios.

In particular, by adapting the log-linearized present-value model we would be able to decompose the variations in capital ratios into three components: the variations in expected future discount rates, future profitability and expected leverage ratios. This decomposition allows us to conduct the variance decomposition to show exactly how much the variations in expected future discount rates and future profitability have contributed to the variations in bank capital ratios respectively. Our empirical results have showed that changes in expected discount rates dominate in the time-series variation of bank capital ratios, while changes in expected future profitability has played an almost equally important role as the expected discount rates in the cross-sectional variations.

Like the remaining tasks leaved by the first two essays, there are still much challenging work to do with bank capital ratios. We need economic models to help understand what the fundamental economic forces is in driving the variation in market-valued capital ratios, for instance. We need economic models to explain why banks with lower capital ratios earn higher expected returns, and why risk factors that help account for the cross-section of bank stock returns would get risk premium. We need to show the mechanisms that generate the observed variation in bank capital ratios by linking the risk premia to fundamental economic factors such as preference, productivity, and economic structure.

The last essay looks at the question about how changes in one stock market could influence the others. In particular, we employ the CCF and multivariate GARCH approaches to investigate the causality-in-variance linkage between Chinese stock markets and major international stock markets by using the daily data of recent two years. We find surprisingly that there is significant empirical evidence to show that the A-shares market of China caused international major markets in variance, indicating the volatility spillover from the former to the latter, while there appears no feedback in variance in the reverse direction. In contrast, the B-shares and H-shares indices of Chinese enterprises, in which more international investors participate, are not only affected by the A-shares, but also significantly sensitive to the U.S. market. The inconsistent results compared with the A-shares market seem to suggest that there may be remarkable distortion in the information enclosure, underestimated risks, or investors with much less risk-aversion in the A-shares market of mainland China, allowing potential room for sudden adjustments.

The last essay could be considered as an attempt to address the question about how information becomes reflected in stock prices. Our analysis is based on the simple idea that information flow may not be reflected in the first-moment (mean) of price changes but in the second-moment (variance) of price changes. On the other hand, there is as well another approach focusing on the relation between stock prices and information-based trading. Empirical results have provided fruitful evidence supporting the claim that the prices and information-based trading are related. In essence, this string of researches associated the prices to the trading volume which is abstract from the current main-stream economic theory. I expects that understanding information-based trading and its price effects could help sharpen our understanding about how information is reflected in stock prices. Therefore, this area could be a potential direction for future researches.

This essay also indicates that discount rate or risk premia variations across different markets could be somehow isolated. Markets could maintain segmented discount rates for a long period of time. However, what I want to emphasize is that this fact does not necessarily mean an "informational inefficiency". In the context of our analysis, the fact that Chinese markets are not incorporating information from other markets, or influenced by other markets, does not necessarily mean the existence of cash flow information not being correctly reflected in stock prices. Anyway, much of the dynamic movement of stock prices corresponds to the variation in discount rates. Stock prices could move much even when there is no cash flow news. Therefore, we could view the volatility spillover effects largely as information transmission about discount rates rather than information about cash flow, whether discount rate variations are connected to the real economy. This question can only be answered by linking asset prices to macroeconomic events, which is on my research agenda for the following years.

Bibliography

Arshanapalli, B. and Doukas, J. (1993) "International stock market linkages: evidence from the pre-and post-October 1987 period," *Journal of Banking and Finance*, Vol. 17, No. 1, pp. 193–208.

Bernanke, B.S. and K.N. Kuttner (2005) "What Explains the Stock Markets Reaction to Federal Reserve Policy," *Journal of Finance*, Vol. 60, No. 3, pp. 1221–1257.

Bhar, R. and Hamori, S. (2006) "Empirical investigation on the relationship between Japanese and Asian emerging equity markets," *Applied Financial Economics Letters*, Vol. 2, No. 2, pp. 77–86.

Boldrin, M., L.J. Christiano, and J.D.M. Fisher (2001) "Habit persistence, asset returns, and the business cycle," *American Economic Review*, pp. 149–166.

Bollerslev, T. and Chou, R.Y. and Kroner, K.F. (1992) "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence," *Journal of Econometrics*, Vol. 52, No. 1, pp. 5–59.

Boudoukh, J., R. Michaely, M. Richardson, and M.R. Roberts (2007) "On the Importance of Measuring Payout Yield: Implications for Empirical Asset Pricing," *The Journal of Finance*, Vol. 62, No. 2, pp. 877–915.

Boudoukh, J., M. Richardson, and R.F. Whitelaw (2008) "The Myth of Long-Horizon Predictability," *Review of Financial Studies*, Vol. 10.

Campbell, John Y and John Ammer (1993) "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns," *The Journal of Finance*, Vol. 48, No. 1, pp. 3–37.

Campbell, J.Y. (1991) "A Variance Decomposition for Stock Returns," *The Economic Journal*, Vol. 101, No. 405, pp. 157–179.

Campbell, J.Y. and Y. Hamao (1992) "Predictable stock returns in the United States and Japan: A study of long-term capital market integration," *Journal of Finance*, pp. 43–69.

Campbell, J.Y. and R. Shiller (1988) "The Dividend Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, Vol. 1, pp. 195–228.

Case, K.E. and R.J. Shiller (1990) "Forecasting Prices and Excess Returns in the Housing Market," *AREUEA Journal*, Vol. 18, No. 3, pp. 253–273.

Chen, Sichong (2008) "Exploring the driving force and price adjustment of the J-REIT market," *Economics Bulletin*, Vol. 7, No. 4, pp. 1-9.

Chen, Sichong (2009) “Capital Ratios and the Cross-Section of Bank Stock Returns.” Japan Society of Monetary Economics, 2009 Spring Conference.

Chen, Sichong and Liu Cheng (2008) 「中国と主要国際金融市場間のリスク・トランスミッション」, *World Economics Papers*, 第5巻.

Chen, Sichong, Liu Cheng, and Tu Hong (2008) “Volatility Spillover between Chinese and Major International Stock Markets: A Causality-in-variance Approach,” *The Empirical Economics Letters*, Vol. 7, No. 11, pp. 1091-1098, November.

Cheung, Yin-Wong and L.K. Ng (1996) “A causality-in-variance test and its application to financial market prices,” *Journal of Econometrics*, Vol. 72, No. 1-2.

Cochrane, J.H. (1992) “Explaining the Variance of Price Dividend Ratios,” *Review of Financial Studies*, Vol. 5, No. 2, pp. 243-280.

Cochrane, J.H. (1994) “Permanent and transitory components of GNP and stock prices,” *The Quarterly Journal of Economics*, pp. 241–265.

Cochrane, J.H. (2005) *Asset Pricing:Revised*, Princeton: Princeton University Press.

Cochrane, J.H. (2008a) “The dog that did not bark: A defense of return predictability,” *Review of Financial Studies*, Vol. 21, No. 4, pp. 1533-1575.

Cochrane, J.H. (2008b) "Financial Markets and the Real Economy," in Mehra, Rajnish ed. *Handbook of the Equity Risk Premium*: Elsevier Science.

Cohen, R.B., C. Polk, and T. Vuolteenaho (2003) "The value spread," *The Journal of Finance*, Vol. 58, No. 2, pp. 609–641.

Corhay, A. and Rad, A.T. and Urbain, J.P. (1995) "Long run behaviour of Pacific-Basin stock prices," *Applied Financial Economics*, Vol. 5, No. 1, pp. 11–18.

Ding, Z, Z Su, and X Du (2007) " spillover and threshold effect: the mechanism of international securities market's risk shock on China," *Management World*, Vol. 1, No. 1, pp. 41–47.

Eetrella, A., S. Park, and S. Peristiani (2000) "Capital Ratios as Predictors of Bank Failure," *FRBNY Economic Policy Review*, Vol. 6, No. 2, pp. 33-52.

Engle, R.F. and Kroner, K.F. (1995) "Multivariate Simultaneous Generalized Arch," *Econometric Theory*, Vol. 11, No. 1, pp. 122–150.

Engle, R.F., T. Ito, and W.L. Lin (1990) "Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market," *Econometrica*, Vol. 58, No. 3, pp. 525–542.

Fama, E.F. (1990) "Stock Returns, Expected Returns, and Real Activity," *The Journal of Finance*, Vol. 45, No. 4, pp. 1089–1108.

Fama, E.F. and K.R. French (1992) “The Cross-section of Expected Stock Returns,” *Journal of Finance*, Vol. 47, pp. 427–465.

Fama, E.F. and K.R. French (1993) “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of financial economics*, Vol. 33, No. 1, pp. 3–56.

Fama, E.F. and K.R. French (1995) “Size and Book-to-market Factors in Earnings and Returns,” *Journal of finance*, pp. 131–155.

Fama, E.F. and K.R. French (1996) “Multifactor Explanations of Asset Pricing Anomalies,” *Journal of Finance*, Vol. 51, pp. 55–84.

Fama, E.F. and K.R. French (2006) “Profitability, investment and average returns,” *Journal of Financial Economics*, Vol. 82, No. 1, pp. 491–518.

Fama, E.F. and K.R. French (2008) “Dissecting anomalies,” *The Journal of Finance*, Vol. 63, No. 4, pp. 1653–1678.

Fama, E.F. and R. French, Kenneth (1988) “Dividend yields and expected stock returns,” *Journal of Financial Economics*, Vol. 22, No. 1, pp. 3–25.

Fama, E.F. and J.D. MacBeth (1973) “Risk, Return, and Equilibrium: Empirical Tests,” *Journal of Political Economy*, Vol. 81, No. 3, p. 607.

Flannery, M.J. (1998) “Using Market Information in Prudential Bank Supervision: A Review of the US Empirical Evidence.,” *Journal of Money, Credit & Banking*, Vol. 30, No. 3, pp. 273-305.

Flannery, M.J. and K.P. Rangan (2008) "What caused the bank capital build-up of the 1990s?," *Review of Finance*, Vol. 12, No. 2, p. 391.

Fu, Y. and L.K. Ng (2001) "Market Efficiency and Return Statistics: Evidence from Real Estate and Stock Markets Using a Present-Value Approach," *Real Estate Economics*, Vol. 29, No. 2, pp. 227–250.

Genesove, D. and C.J. Mayer (1997) "Equity and Time to Sale in the Real Estate Market," *The American Economic Review*, Vol. 87, No. 3, pp. 255–269.

Ghosh, A. and Saidi, R. and Johnson, K.H. (1999) "Who Moves the Asia-Pacific Stock Markets-US or Japan? Empirical Evidence Based on the Theory of Cointegration," *The Financial Review*, Vol. 34, No. 1, pp. 159–169.

Glascock, J.L., C. Lu, and R.W. So (2000) "Further Evidence on the Integration of REIT, Bond, and Stock Returns," *The Journal of Real Estate Finance and Economics*, Vol. 20, No. 2, pp. 177–194.

Goyal, A. and I. Welch (2003) "Predicting the equity premium with dividend ratios," *Management Science*, pp. 639–654.

Green, W. (2003) *Econometric analysis, 5th ed*: Prentice Hall, New Jersey.

Groenewold, N., S.H.K. Tang, and Y. Wu (2004) "The dynamic interrelationships between the greater China share markets," *China Economic Review*, Vol. 15, No. 1, pp. 45–62.

Grubel, H.G. and Fadner, K. (1971) "The Interdependence of International Equity Markets," *The Journal of Finance*, Vol. 26, No. 1, pp. 89–94.

Hafner, C.M. and H. Herwartz (2004) "Testing Causality in Variance Using Multivariate GARCH Models." Econometric Institute Report 20, Erasmus University Rotterdam.

Hall, Robert E. (2001a) "The Stock Market and Capital Accumulation," *American Economic Review*, Vol. 91, No. 5, pp. 1185-1202.

Hall, Robert E. (2001b) "Struggling to Understand the Stock Market," *American Economic Review*, Vol. 91, No. 2, pp. 1–11.

Hamao, Y. (1991) "A standard data base for the analysis of Japanese security markets," *The Journal of Business*, Vol. 64, No. 1, pp. 87–102.

Hamori, S. (2003) *An Empirical Investigation of Stock Markets: The CCF Approach*: Kluwer Academic Publishers.

Harvey, C.R. (1991) "The World Price of Covariance Risk," *The Journal of Finance*, Vol. 46, No. 1, pp. 111–157.

Hayek, F.A. (1945) "The Use of Knowledge in Society," *American Economic Review*, Vol. 35, pp. 519–530.

Hodrick, RJ (1992) "Dividend yields and expected stock returns: Alternative procedures for inference and measurement," *Review of Financial studies*, Vol. 5, No. 3, pp. 357–386.

Hong, Y. (2001) “A test for volatility spillover with application to exchange rates,” *Journal of Econometrics*, Vol. 103, No. 1-2.

Hong, Y, S Cheng, Y Liu, and S Wang (2004) “Extreme Risk Spillover between Chinese Stock Market and Internati0nal Stock Markets,” *China Economic Quarterly*, Vol. 3, No. 003, pp. 703–726.

Hoshi, T. (1986) “A test of stock price volatility: The case of Japan,” *Financial Research*, Vol. 5, pp. 1–18.

Hu, J.W.S., M.Y. Chen, R.C.W. Fok, and B.N. Huang (1997) “Causality in volatility and volatility spillover effects between US, Japan and four equity markets in the South China Growth Triangular,” *Journal of International Financial Markets, Institutions & Money*, Vol. 7, No. 4, pp. 351–367.

Huang, Bwo-Nung, Chin-Wei Yang, and John Wei-Shan Hu (2000) “Causality and cointegration of stock markets among the United States, Japan and the South China Growth Triangle,” *International Review of Financial Analysis*, Vol. 9, No. 3, pp. 281-297.

Jermann, U.J. (1998) “Asset pricing in production economies,” *Journal of Monetary Economics*, Vol. 41, No. 2, pp. 257–275.

Keeley, M.C. (1990) “Deposit insurance, risk, and market power in banking,” *The American Economic Review*, Vol. 80, No. 5, pp. 1183–1200.

Konishi, M. and Y. Yasuda (2004) "Factors Affecting Bank Risk Taking: Evidence from Japan," *Journal of Banking and Finance*, Vol. 28, No. 1, pp. 215–232.

Koop, G. (1994) "An objective Bayesian analysis of common stochastic trends in international stock prices and exchange rates," *Journal of Empirical Finance*, Vol. 1, No. 3-4, pp. 343–364.

Kwan, ACC (1995) "The causal relationships between equity indices on world exchanges," *Applied Economics*, Vol. 27, No. 1, pp. 33–27.

Larrain, B. and M. Yogo (2008) "Does firm value move too much to be justified by subsequent changes in cash flow?," *Journal of Financial Economics*, Vol. 87, No. 1, pp. 200–226.

Laurence, M., F. Cai, and S. Qian (1997) "Weak-form efficiency and causality tests in Chinese stock markets," *Multinational Finance Journal*, Vol. 1, No. 4, pp. 291–307.

LeRoy, S.F. and R.D. Porter (1981) "The present-value relation: Tests based on implied variance bounds," *Econometrica*, pp. 555–574.

Levy, H. and Sarnat, M. (1970) "International Diversification of Investment Portfolios," *The American Economic Review*, Vol. 60, No. 4, pp. 668–675.

Lewellen, J. (2004) "Predicting returns with financial ratios," *Journal of Financial Economics*, Vol. 74, No. 2, pp. 209–235.

Marcus, A.J. (1983) “The Bank Capital Decision: A Time Series–Cross Section Analysis,” *The Journal of Finance*, Vol. 38, No. 4, pp. 1217–1232.

Ohashi, Kamida, and Mori (2003) “The Analysis of J-REIT’s Return and Risk (in Japanese),”Technical report, The Policy Research Institute for Land, Infrastructure and Transport under the Ministry of Land, Infrastructure and Transport.

Payne, J. and Mohammadi, H. (2004) “The Transmission of Shocks across Real Estate Investment Trust (REIT) Markets,” *Applied Financial Economics*, Vol. 14, No. 17, pp. 1211–1257.

Petersen, M.A. (2009) “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches,” *Review of Financial Studies*, Vol. 22, No. 1, pp. 435-480.

Ross, S.A. (1989) “Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy,” *The Journal of Finance*, Vol. 44, No. 1, pp. 1–17.

Santos, Joäo A. C. (2000) “Bank capital regulation in contemporary banking theory: a review of the literature,” Sep.

Seck, D. (1996) “The Substitutability of Real Estate Assets.,” *Real Estate Economics*, Vol. 24, No. 1.

Shiller, Robert J (1981) “Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?” *American Economic Review*, Vol. 71, No. 3, pp. 421-36.

Shimizu, Y (2006) “Real Estate Prices and the Financial Market,” *Review of Monetary and Financial Studies*, Vol. 23, No. 1, pp. 1–14.

Shimizu, Y. (2007a) “Impacts of the BIS regulation on the Japanese economy,” *Journal of Asian Economics*, Vol. 18, No. 1, pp. 42–62.

Stambaugh, R.F. (1999) “Predictive regressions,” *Journal of Financial Economics*, Vol. 54, No. 3, pp. 375–421.

Tallarini, T.D. (2000) “Risk-sensitive real business cycles,” *Journal of Monetary Economics*, Vol. 45, No. 3, pp. 507–532.

Tuluca, S.A. and Zwick, B. (2001) “The Effects of the Asian Crisis on Global Equity Markets,” *The Financial Review*, Vol. 36, No. 1, pp. 125–142.

Van Dijk, D. and Osborn, D.R. and Sensier, M. (2005) “Testing for causality in variance in the presence of breaks,” *Economic Letters*, Vol. 72, pp. 193–199.

Vuolteenaho, T. (2000) “Understanding the aggregate book-to-market ratio.” Working Paper, Harvard University Department of Economics.

Vuolteenaho, T. (2002) “What drives firm-level stock returns?,” *Journal of Finance*, pp. 233–264.

Welch, I. (2004) "Capital Structure and Stock Returns," *Journal of Political Economy*, Vol. 112, No. 1, pp. 106–131.

Yang, J. and Min, I. and Li, Q. (2003) "European Stock Market Integration: Does EMU Matter?," *Journal of Business Finance & Accounting*, Vol. 30, No. 9-10, pp. 1253–1276.

Zivot, E. and Wang, J. (2006) *Modeling Financial Time Series with S-plus, 2nd ed*: Springer.

植田和男・鈴木勝・田村達朗 (1986) 「配当と株価: シラー・テストの日本への応用」,『フィナンシャル・レビュー』, 第 August 巻, 1–10 頁.

清水啓典 (2004) 「自己資本比率規制：理論と現実」. 日本金融学会 2004 春季大会報告論文.

清水啓典 (2005) 「デフレ脱却と BIS 規制」,『商学論纂』, 第 46 巻, 第 3 号, 41-79 頁.

清水啓典 (2006) 「大会・会長講演　不動産価格と金融市場」,『金融経済研究』, 第 23 巻, 1–14 頁.

清水啓典 (2007b) 「BIS 規制と市場評価」,『証券アナリストジャーナル』, 第 45 巻, 第 4 号, 19-33 頁.

青野幸平 (2008) 「日本の株式市場の予測可能性」,『現代ファイナンス』, 第 24 巻, 23-43 頁.

堀敬一 (1999) 「資産価格モデルの実証分析: 展望」,『現代ファイナンス』, 第 6 巻, 47–97 頁.