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Qianying Zhang
Florida International University, qzhan009@fiu.edu

DOI: 10.25148/etd.FIDC001912

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FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

THREE ESSAYS IN FINANCIAL ECONOMICS

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Qianying Zhang

2017

To: Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

This dissertation, written by Qianying Zhang, and entitled Three Essays in Financial Economics, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Mihaela I. Pintea

Brice Dupoyet

Cem Karayalcin

Sheng Guo

Xiaoquan Jiang, Major Professor

Date of Defense: May 26, 2017

The dissertation of Qianying Zhang is approved.

Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

Andrés G. Gil
Vice President for Research and Economic Development
and Dean of the University Graduate School

Florida International University, 2017

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DEDICATION

This dissertation is dedicated to my beloved parents, especially my mother. Her loving kindness will always be with me. Thank you for all the patience, support, encouragement, and love.

ACKNOWLEDGMENTS

I wish to express my deep appreciation and gratitude to my major advisor, Dr. Xiaoquan Jiang, for the mentorship and guidance he provided to me in my academic pursuit. I am truly grateful to have had the opportunity to work with him and learn from him. I would also like to thank all the members of my committee, Dr. Mihaela Pintea, Dr. Brice Dupoyet, Dr. Cem Karayalcin and Dr. Sheng Guo, for their insightful comments and support.

At the same time, I would like to thank Dr. Jesse Bull, Dr. John Boyd, Dr. Hakan Yilmazkuday and all other faculty members from Economics Department and Finance Department for their dedication during my Ph.D. studies at Florida International University. I am also grateful to the following former and current staff at the Department of Economics for their generous support during my graduate studies – Mariela Delgado, Mayte Rodriguez, Maria Cossio, and Lorette Garcia.

I would also like to acknowledge the research guidance and support from my co-authors Dr. Xiaoquan Jiang, Dr. Brice Dupoyet, Dr. William Hardin III, Dr. Zhonghua Wu.

Finally, I would like to thank FIU's University Graduate School for the support provided through the Presidential Fellowship from Fall 2011 to Summer 2013.

ABSTRACT OF THE DISSERTATION

THREE ESSAYS IN FINANCIAL ECONOMICS

by

Qianying Zhang

Florida International University, 2017

Miami, Florida

Professor Xiaoquan Jiang, Major Professor

The dissertation consists of three papers in Financial Economics.

The first paper revisits the link between interest rates and corporate bond credit spreads by applying Rigobon's (2003) heteroskedasticity identification methodology. This novel approach allows us to account for endogeneity problems and to conclude that credit spreads respond negatively to interest rates, a result consistent with the implications of Merton's (1974) structural model. The negative relation is robust to macroeconomic shocks, interest rates characteristics, different volatility regimes, and bond ratings. To explain the negative relation, we rule out the plausibility of callability and business cycle as origins of the negative relationship.

The second paper investigates the assumption that financial asset prices including stocks and bonds, reflect intrinsic value. The commercial real estate market's long-term use of both judgment (appraisal) based returns and transaction returns provides a test of the role of intrinsic value. Statistically significant results from cointegrating models suggest that transaction based returns deviate from judgment based returns in the short run, but converge back to the equilibrium state. Additional tests show that the cointegrating residuals among transaction, appraisal and REITs returns predict the next period

transaction returns. The transaction or price returns are predictable with convergence to intrinsic value. The market moves to intrinsic value.

The third paper decomposes the stock price into fundamental permanent, fundamental transitory, and non-fundamental shocks in order to explore the determinants of stock price fluctuations. The signal extraction model can incorporate the investor's signal extraction process, which allows us to estimate the parameters of cash flow news and discount rate news and decompose stock price more accurately. The results show that the fundamental permanent shock and non-fundamental shock each contribute half to the fluctuation of stock prices while the fundamental transitory shock almost does not play a role in stock price fluctuations. Also, using the measure of time varying risk, we further decompose the non-fundamental component into time varying risk and noise and find that 30% of non-fundamental shock can be explained by the time varying risk shock.

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CHAPTER 1 : A NEW TAKE ON THE RELATIONSHIP BETWEEN INTEREST RATES AND CREDIT SPREADS

1.1 Introduction

The relation between interest rates and credit spreads has been a subject of debate since Merton's (1974) proposed structural model for corporate bond valuation. Identifying the response of credit spreads to changes in interest rates is a challenging task for two main reasons. One issue is that credit spreads and interest rates endogenously react to one another. For instance, a change in interest rates is, ceteris paribus, associated with a change in bond market prices, and thus correspondingly with a possible change in credit spread. Meanwhile, Federal Reserve policy makers may react to credit spread shocks - due to liquidity, inflation, risk, or growth concerns for instance –by taking actions that result in a change in interest rates. The observed credit spreads and interest rates are therefore simultaneously determined by the interaction of the two schedules.

The second issue is that of the confounding factors problem. The co-movements of interest rates and credit spreads are likely influenced by a certain set of macroeconomic common shocks or preference shifting, rendering the disentangling of the two problems. All in all, these two issues complicate the studying of the response of credit spreads to interest rate changes, and might also explain the conflicting findings found in the literature. Merton's view hinges on the proposition that debt can be viewed as a contingent claim on the underlying firm value. Merton's structural model states that when interest rates are raised, under risk-neutral valuation the expected future value of the firm's assets increases, leading to a lower probability of default and thus to lower corporate credit spreads. Subsequent research at times validates Merton's prediction of a negative relation between interest rates and credit spreads. Kim, Ramaswarmy and Sundaresan (1993) develop a contingent-claims model with stochastic interest rates, obtaining a negative relationship between interest rates and corporate spreads for all bond maturities. Extending the Black and Cox (1976) model by incorporating default and interest risks, Longstaff and Schwartz (1995) also find

that credit spreads are negatively related to interest rates, with their closed-form corporate debt valuation framework attributing the negative relation to both an asset-value factor and an interest-rate factor. Other studies confirming the result include Longstaff and Schwartz (1995), Collin-Dufresne Goldstein and Martin (2001), Campbell and Taksler (2003), and Avramov, Jostova and Philipov (2007).

Duffee (1998), however, argues that the callability feature plays an important role in the inverse relation between interest rates and credit spreads. The rationale is the fact that when interest rates increase, callable bonds are less likely to be called and their credit spreads should therefore see a decrease relative to their levels prior to the interest rate rise. Furthermore, Jacoby, Liao, and Batten (2007) find the negative relation between interest rates and credit spreads severely weakened once callable bonds are excluded from the sample. Others such as Neal, Rolph, Dupoyet and Jiang (2015) find a negligible relationship after conditioning on interest rates and market conditions.

Lastly, some research supports the idea that an increase in the risk-free rate induces a widening of credit spreads. The positive relation is predicted under certain conditions by models such as the dynamic optimal capital structure model of Leland and Toft (1996) or Goldstein, Ju and Leland (2001). The positive relationship is also supported by Bevan and Garzarelli (2000) as well as Davies (2008) who conclude that an increase in interest rates induces a positive change in credit spreads in both the short run and the long run, casting additional doubt as to the sign of the relation.

The subject has some important portfolio and risk management implications. If credit spreads do indeed shrink when interest rates rise, as Merton (1974) or Longstaff and Schwartz (1995) predict, the changes in corporate bond yields of a given maturity will depend on the magnitude of the credit spreads changes. If, on the other hand, the arguments put forward by Neal et al. (2015) are confirmed, in an instance of rising interest rates, corporate bonds negative percentage changes in price should be of about the same magnitude as those of Treasury bonds of equivalent duration. Finally, if, as Leland and Toft (1996) and others suggest, there is a positive relation between interest

rates and credit spreads, corporate bonds yields should increase more than Treasury rates of similar duration, implying that corporate bonds negative percentage changes in price should be of greater magnitude than those of Treasury bonds of equivalent duration. We detail the various possible scenarios in the Appendix.

We tackle the endogeneity problem by applying Rigobon's (2003) "identification through heteroskedasticity" method to the possibly bidirectional interest rate - credit spread relationship. This approach allows parameter identification through the shifting of the variance of the shocks, dealing with the endogeneity issue when other identification methods would otherwise not be appropriate. Applied in this setting, the identification through heteroskedasticity method delivers consistent and robust estimates of the credit spreads' reaction to interest rates. We find a negative response of credit spreads to interest rates, as implied by Merton (1974) structural model. The negative relation is of economic and statistical significance, robust to common shocks, interest rates characteristics, different volatility regimes, callability features, and bond credit ratings. We also find that the magnitude of the negative relation is larger for high-yield bonds than for investment-grade bonds, a sensible result since riskier bonds are in general more sensitive to a changing economic environment.

Finally, we reexamine several existing explanations for the negative relation. First, we show that the negative relationship remains statistically significant even when the methodology is applied to a bond index devoid of any callability features, supporting King's (2002) argument that callable bonds are not necessarily largely responsible for the negative relation between interest rates and credit spreads and that the effect persists even when they are removed from the sample. Collin-Dufresne et al (2001) argue that business climate change is a significant determinant of credit spreads. Superficially, the negative relationship might be due to investors' perception of economic growth and risk related to business cycles. During a period of economic expansion, interest rates generally gradually rise, and as the economic environment continues to improve, corporate risk

largely goes down and corporate bond default risk premiums tend to decrease, thus lowering credit spreads. Conversely, during a period of economic contraction, interest rates are likely gradually decreased by the Federal Reserve, and as the economic environment keeps worsening, corporate risk goes up and corporate bond default risk premiums generally tend to rise, increasing credit spreads. We further test this intuition by using a two-step procedure. Interest rate and credit spread changes are first made orthogonal to changes in various macroeconomic variables and business cycle effects and are then run through the identification through heteroskedasticity procedure. Our results confirm with high statistical significance that, even when macroeconomic variables and business cycles are excluded from interest rates and credit spreads, a similar negative relationship remains.

This paper casts a fresh eye on the debate over the interest rates - credit spreads relation and contributes to the literature in several ways. First, to the best of our knowledge, this is the first paper to address the endogeneity problem found in the dynamics between credit spreads and interest rates. Second, contrary to the findings of Jacoby et al. (2007), we show the negative relation to be economically and statistically significant and robust for all bond indices, even though the reaction of credit spreads to interest rate changes is indeed slightly lower when callable bonds are excluded from the sample. Our empirical results are in fact consistent with Duffee (1998) and King (2002).[1] Finally, we examine the business cycle explanation for the negative relationship between interest rates and credit spreads by testing whether the negative relation survives after the macroeconomic variables and business cycle effects are removed, and show that the negative relationship subsists.

The remainder of this paper is organized as follows. Section 1.2 introduces the methodology used to identify the parameters through heteroskedasticity and the data employed in this study. Section 1.3 describes the different models estimated and the corresponding empirical estimates of

[1] King (2002) estimates that the call option value only makes up about two percent of the par value of the average callable bond.

the relationship between interest rates and credit spreads. Section 1.4 explores the validity of two additional possible explanations for the negative relation, and section 1.5 concludes.

1.2 Methodology and Data

In this section, we describe the methodology and data used in our empirical tests. The technique used in these different exercises follows Rigobon's (2003) method of identification through heteroskedasticity, a procedure that allows one to account for endogeneity issues and properly capture the interaction between interest rates and credit spreads.

1.2.1. Methodology

When empirically estimating the relation between credit spreads and interest rates, one faces an identification challenge since both credit spreads and interest rates are endogenous variables. We address this concern by applying the heteroskedasticity identification method developed by Rigobon (2003). The fundamental idea behind identification through heteroskedasticity is that with structural parameters remaining stable across different regimes, variances of structural shocks in the regimes provide additional restrictions, leading to the identification of the system. The key assumption is that the variances of structural shocks in regimes cannot change proportionally. In order to apply this method successfully, one must therefore ensure that the structural shocks exhibit some non-proportional heteroskedasticity. We first consider a simple bivariate VAR model without common shocks, and subsequently take various macroeconomic common shocks into account as well.

We first establish a structural bivariate VAR system to capture the interaction between interest rates and credit spreads:

$$CS_t = \alpha TB_t + \sum_{k=1}^{n} \xi_k TB_{t-k} + \sum_{k=1}^{n} \theta_k CS_{t-k} + \upsilon_t \tag{1.1}$$

$$TB_t = \beta CS_t + \sum_{k=1}^{n} \kappa_k CS_{t-k} + \sum_{k=1}^{n} \lambda_k TB_{t-k} + \mu_t \tag{1.2}$$

where TB_t and CS_t designate the Treasury Bill rates and Corporate Bond credit spreads respectively, and where υ_t and μ_t are the structural shocks for credit spreads and interest rates. The index k represents the number of lag terms, α stands for the impact of interest rates on credit spreads, and β represents the interest rate sensitivity to credit spreads. The contemporaneous reaction of credit spreads to interest rates, α, is the parameter in which we are most interested.

It is however well known that these coefficients cannot be estimated directly due to the endogeneity of the regressors. The usual approach to get around an endogeneity issue is to impose an instrumental variable or additional parameter restriction (for instance, an exclusion restriction, a sign restriction, or a long-run restriction). In this case, however, it is challenging to find an instrumental variable affecting only interest rates and not credit spreads, for the simple reason that both interest rates and credit spreads are both influenced by a set of common macroeconomic factors. No economic or finance theory can help impose additional restrictions in this case. In order to deal with these endogeneity issues, one must therefore resort to an alternative identification technique. The heteroskedasticity in the residuals of interest rates and credit spreads is used here to identify the α and β parameters.

If we insert TB_t in (1.2) into (1.1) and CS_t in (1.1) into (1.2), respectively, we obtain the reduced-form equations (1.3) and (1.4):

$$CS_t = \frac{1}{1-\alpha\beta}[\sum_{k=1}^{n}(\alpha\lambda_k + \xi_k)TB_{t-k} + \sum_{k=1}^{n}(\alpha\kappa_k + \theta_k)CS_{t-k} + (\alpha\mu_t + \upsilon_t)] \tag{1.3}$$

$$TB_t = \frac{1}{1-\alpha\beta}[\sum_{k=1}^{n}(\beta\xi_k + \lambda_k)TB_{t-k} + \sum_{k=1}^{n}(\beta\theta_k + \kappa_k)CS_{t-k} + (\mu_t + \beta\upsilon_t)] \tag{1.4}$$

where $\frac{1}{1-\alpha\beta}(\alpha\mu_t + \upsilon_t)$ and $\frac{1}{1-\alpha\beta}(\mu_t + \beta\upsilon_t)$ are the residuals of the reduced-form equations (1.3) and (1.4).

Based on the reduced-form VAR system, we can estimate the variance-covariance matrix of equations (1.3) and (1.4) determined by:

$$\Omega = \frac{1}{(1-\alpha\beta)^2}\begin{pmatrix} \sigma_v^2 + \alpha^2\sigma_\mu^2 & \beta\sigma_v^2 + \alpha\sigma_\mu^2 \\ & \beta^2\sigma_v^2 + \sigma_\mu^2 \end{pmatrix} \tag{1.5}$$

The variance-covariance matrix offers three equations, while there are four parameters to be estimated: $\alpha, \beta,\ \sigma_v^2,$ and σ_μ^2. The system is clearly under-justified and at least one additional equation is required to identify the system. We consider two regimes based on the different variance characteristics of the two structural shocks μ_t and v_t. However, it is necessary to assume that the α and β parameters remain stable across the different regimes and that the structural shocks are not correlated. For each regime, we have:

$$\Omega_i = \begin{pmatrix} \Omega_{11,i} & \Omega_{12,i} \\ & \Omega_{22,i} \end{pmatrix} = \frac{1}{(1-\alpha\beta)^2}\begin{pmatrix} \sigma_{v,i}^2 + \alpha^2\sigma_{\mu,i}^2 & \beta\sigma_{v,i}^2 + \alpha\sigma_{\mu,i}^2 \\ & \beta^2\sigma_{v,i}^2 + \sigma_{\mu,i}^2 \end{pmatrix} \tag{1.6}$$

where each regime is represented by i = {1,2}

There are six equations provided by the variance-covariance matrices in the two regimes and six unknown parameters: $\alpha, \beta, \sigma_{v,1}^2, \sigma_{v,2}^2,\ \sigma_{\mu,1}^2,$ and $\sigma_{\mu,2}^2$. If the six equations are independent, then the parameters are just-identified. Solving from matrix (1.6), α and β must satisfy:

$$\alpha = \frac{\Omega_{12,i} - \beta\Omega_{11,i}}{\Omega_{22,i} - \beta\Omega_{12,i}} \tag{1.7}$$

where i= {1,2}

The β parameter can then be solved from the following equation:

$$(\Omega_{11,1}\Omega_{12,2} - \Omega_{12,1}\Omega_{11,2})\beta^2 - (\Omega_{11,1}\Omega_{22,2} - \Omega_{22,1}\Omega_{11,2})\beta + (\Omega_{12,1}\Omega_{22,2} - \Omega_{22,1}\Omega_{12,2}) = 0. \tag{1.8}$$

Rigobon (2003) shows that the α and β parameters can be consistently estimated from the variance-covariance matrices of the two regimes.[2] It is worth noting that consistency can be still

[2] See proposition 1 in Rigobon (2003, pp. 780).

achieved under some misspecification of the heteroskedasticity.[3] In this paper, we estimate these parameters using Hansen's (1982) Generalized Method of Moments (GMM). To address potential small-sample bias concerns, we additionally implement a bootstrapping procedure and report the bootstrapped p-values for each estimate. The bootstrapping procedure involves simulating historical data for the variables and then using these simulated time series to generate the parameters distributions through the same estimation method applied to actual historical data. Our bootstrapping procedure consists of the following four steps. First, we begin by estimating the VAR system described in equations (1.3) and (1.4) and store the reduced-form residuals for resampling. Then the parameter α and β are estimated by GMM using the identification through heteroskedasticity method. Second, we randomly draw from the stored residuals in each regime and generate two bootstrapped time series $\widehat{\mathrm{CS}}_{\mathrm{t}}$ and $\widehat{\mathrm{TB}}_{\mathrm{t}}$ in the reduced-form VAR system. In the third step, using the bootstrapped series $\widehat{\mathrm{CS}}_{\mathrm{t}}$ and $\widehat{\mathrm{TB}}_{\mathrm{t}}$, we re-estimate the α and β parameters via the identification through heteroskedasticity procedure. The fourth step involves repeating steps 2 and 3 one thousand times and storing the bootstrapped parameter estimate α for each iteration. Finally, the bootstrapped p-values of the α parameter are reported.

Interest rates time series are known to exhibit fairly long up and down swing patterns. Figure 1.1 shows that the variations in interest rates are largely upward before 1981 and largely downward after 1981. Figure 1 also already hints graphically at the inverse nature of the relationship between interest rates and credit spreads, particularly during recessions. This pattern suggests that interest rates have both a slow mean-reverting component[4] and a more rapid (business-cycle-length) mean-reverting element. In order to capture the slow mean-reverting effect, we follow Fama (2006) and

[3] See proposition 3 and 4 in Rigobon (2003, pp.783-784).

[4] There are slightly differing opinions on the slow mean reversion of interest rates. Duffee (2002) interprets the slow mean reversion of interest rates as a result of a near-permanent shock, while Fama (2006) argues that it is due to a permanent shock.

consider three approaches. The first approach is to add a dummy variable D in the VAR system in equations (1.1) and (1.2). The dummy variable D is equal to one for data before August 1981 (when interest rates peak), and zero otherwise. This interest rate dummy variable enables us to distinguish between upward and downward periods, and the equations become:

$$CS_t = \alpha TB_t + \sum_{k=1}^{n} \xi_k TB_{t-k} + \sum_{k=1}^{n} \theta_k CS_{t-k} + \phi_1 D_t + \upsilon_t \tag{1.9}$$

$$TB_t = \beta CS_t + \sum_{k=1}^{n} \kappa_k CS_{t-k} + \sum_{k=1}^{n} \lambda_k TB_{t-k} + \psi_1 D_t + \mu_t \tag{1.10}$$

The second approach is to decompose interest rates into a long-term expected value (K_t) measured as a five-year moving average of interest rates, and a local mean-reverting component (X_t), measured as the difference between current interest rates (TB_t) and the long-term mean-reverting level (K_t). Adding X_t into the VAR system allows us to take into account the local mean-reverting effect, yielding the following system:

$$CS_t = \alpha TB_t + \sum_{k=1}^{n} \xi_k TB_{t-k} + \sum_{k=1}^{n} \theta_k CS_{t-k} + \phi_2 X_t + \upsilon_t \tag{1.11}$$

$$TB_t = \beta CS_t + \sum_{k=1}^{n} \kappa_k CS_{t-k} + \sum_{k=1}^{n} \lambda_k TB_{t-k} + \psi_2 X_t + \mu_t \tag{1.12}$$

The third approach is to combine the first two. Including a dummy variable and a local mean-reverting component yields the following equations:

$$CS_t = \alpha TB_t + \sum_{k=1}^{n} \xi_k TB_{t-k} + \sum_{k=1}^{n} \theta_k CS_{t-k} + \phi_1 D_t + \phi_2 X_t + \upsilon_t \tag{1.13}$$

$$TB_t = \beta CS_t + \sum_{k=1}^{n} \kappa_k CS_{t-k} + \sum_{k=1}^{n} \lambda_k TB_{t-k} + \psi_1 D_t + \psi_2 X_t + \mu_t \tag{1.14}$$

In the above bivariate VAR models, we assume that the structural shocks are orthogonal, implying that the structural VAR system does not allow common shocks. Rigobon (2003) demonstrates that in a bivariate VAR setting with unobservable common shocks, heteroskedasticity alone will not be sufficient to achieve identification. Additionally, failing to take these common shocks into account may lead to spurious estimations. We therefore proceed to achieve identification through heteroskedasticity and the use of additional observable common shocks, since many studies in the literature have shown that macroeconomic variables affect both interest rates and credit spreads (Altman, Brady, Resti, and Sironi (2005), Ang and Piazzesi (2003), Langstaff and Schwartz (1995) and Wu and Zhang (2008) to name a few). We select inflation, unemployment rate, economic growth, personal income, consumer expenditure, and stock market excess returns as the main common shocks.

1.2.2 Data

We obtain monthly yields on Barclay bond indices from Datastream and 3-month Treasury bill rates from the Saint Louis Federal Reserve, with the corporate bond investment-grade index spanning from 1973.1 to 2014.12 and the corporate bond high-yield index spanning from 1987.1 to 2014.12. In order to test whether the callability feature of bonds might be responsible for the negative relation between interest rates and credit spreads, we also use the Bank of America - Merrill Lynch Aggregate Corporate Bond Index and the Corporate Bond Index that specifically excludes Yankee and optionable bonds, with data spanning from 1995.1 to 2014.12.

The Consumer Price Index (CPI), Unemployment Rate (UER), Industrial Productivity Index (IPI), Personal Disposable Income (PDI) and Personal Consumer Expenditure (PCE) are obtained from the Saint Louis Federal Reserve. The UER, IPI, PDI, and PCE are monthly percentage changes of the respective variables. Inflation (INF) is the CPI monthly percentage change. Stock market excess returns (RMRF) are the value-weighted returns on all NYSE, AMEX, and NASDAQ

stocks (from CRSP) minus the one-month Treasury bill rate. Macroeconomic common shocks are measured as residuals of AR (1) processes fitted to each macroeconomic variable.

1.3 Relationship between Interest Rates and Credit Spreads

1.3.1 Properties of Interest Rates and Credit Spreads

Table 1.1 summarizes the monthly statistics for Treasury rates, credit spreads for investment-grade and high-yield bonds, inflation rates, CRSP value-weighted market excess returns, the Unemployment Rate, Industrial Productivity Index, Personal Disposable Income, Personal Consumer Expenditure, and in some cases their respective first differences or percentage changes. Treasury bill rates exhibit a wide spectrum of levels, ranging from 0.01% to 16.3%, with their first differences indicating gradual monthly changes averaging about -0.01% per month, extending from -4.62% (an extreme outlier in May of 1980) to 2.61%. Investment-grade and high-yield corporate spreads average about 2.8% and 7.1% respectively, with their monthly first differences near zero but stretching over a range of -3.11% to 3.86% and -2.94% to 5.22% respectively. Monthly average inflation is about one third of a percent with a tight range, while monthly stock market excess returns - although on average close to half a percent - experience a very large array of values going from -23% to 16%.

We then test for the presence of a unit root in both the interest rates and credit spreads time series. Table 1.2 reports the results for the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests with a constant and a trend. The null hypothesis of a unit root is rejected at the 10 percent significance level for Treasury rates and at the 1 percent significance level for investment-grade credit spreads in both ADF and PP tests. For high-yield credit spreads, the null hypothesis of a unit root is rejected at the 10 percent significance level in the ADF test but cannot be rejected at the 10% level in the PP test. It is well known that standard unit root tests can lack power (a type II error) and the results in Table 1.2 do not indeed provide a definite conclusion, but they overall do tend to

reject the unit root hypothesis. Since a non-stationary process implies an explosive volatility structure over time, Joutz, Mansi and Maxwell (2001) argue that interest rates and credit spread cannot plausibly be non-stationary over long periods of time. Facing a similar issue on the time-series properties of book-to-market ratios, Vuolteenaho (2000) states "I am forced to base the stationarity assumption more on economic intuition than on the clear-cut rejection of unit root tests." However, simulations in Granger and Newbold (1974) also show that statistically significant results and high R squares can be obtained when two unrelated but highly persistent time series are regressed on one another, indicating that failing to take their persistence into account could lead to spurious conclusions. Granger and Newbold (1974) suggest that the rule should rather be to work with both levels and changes, and to subsequently interpret the combined results. Following Granger and Newbold (1974), we therefore use both levels and changes of interest rates and credit spreads in our estimations. The results with levels and changes are similar. In the interest of space, we report the results pertaining to the changes in interest rates and credit spreads and leave the results with levels available upon request.

1.3.2. Relation between Changes in Interest Rates and Credit Spreads: The Base Model

We begin with the base model without common shocks. The first step is to estimate the residual vector $[(\alpha\mu_t + \upsilon_t)/(1-\alpha\beta), (\mu_t + \beta\upsilon_t)/(1-\alpha\beta)]'$ of the reduced-form bivariate VAR model in equations (3) and (4). Using the Bayesian Information Criterion, we identify a number of three lags as optimal for the investment-grade bond VAR, and a number of two lags for the high-yield bond VAR. The heteroskedasticity identification approach is motivated by the different variances of the residual vectors under different regimes. The key element in the identification process is to divide the sample into different regimes. Volatility regimes can be split in a variety of ways, all appropriate as long as the ratio of the variance of interest rate shocks in regime one ($\Omega_{11,1}$) to the

variance of interest rate shocks in regime two ($\Omega_{11,2}$) remains different from the ratio of the covariance between interest rate shocks and credit spreads shocks in regime one ($\Omega_{12,1}$) to the covariance between interest rate shocks and credit spreads shocks ($\Omega_{12,2}$) in regime two. One implication is that if interest rate shocks become more volatile, the reaction of credit spreads to those interest rates will have a larger effect on the covariance between interest rates and credit spreads.

We define regimes according to the size and direction of the variance of the residuals in the reduced-form model, with the different regimes affecting the coefficients in distinct ways. Interest rates and credit spreads are in regime I when both shocks are above one standard deviation over the mean. Interest rates and credit spreads are in regime II when both shocks are below one standard deviation under the mean. Finally, interest rates and credit spreads are in regime III when both shocks are within one standard deviation of the mean. Regimes I and II both capture high volatility regions of the distribution, with regime I pertaining to the upper tail and regime II to the lower tail of the distribution, while regime III captures the lower volatility region of the distribution. There are therefore two possible subsets associated with these three regimes, denoted from here on as [regime I&III] and [regime II&III]. Adopting this regime segregation method allows the capturing of the asymmetric effects of shocks on the interest rate-credit spread relation. Additionally, the different standard deviations of interest rates and credit spreads provide favorable conditions for an estimation through heteroskedasticity since the variances of interest rate shocks and credit spread shocks are not proportional. If the identification through heteroskedasticity approach performs well, results from an estimation based on Regime I&III should be very similar to those of an estimation based on Regime II&III. The estimates from these two subsets are shown in Table 1.3.

Table 1.3 reports results associated with the four models estimated on the investment-grade corporate bond index and the two models estimated on the high-yield bond index using changes in interest rates and credit spreads. We do not implement the dummy variable for high-yield bonds

(Panel B) since our sample for the high-yield bond index starts in September of 1981 only. Table 1.3 shows that interest rates have a significant impact on credit spreads for both investment-grade and high-yield bonds. In Panel A, for investment-grade bonds, under Regime I&III the estimated α (credit spreads' reaction to interest rates) is -0.950 with a t-statistic of -9.716 and a bootstrapped p-value of 0.000 in the base model, -0.944 with a t-statistic of -9.461 and a bootstrapped p-value of 0.001 when adding the dummy variable to the base model, -0.935 with a t-statistic of -9.168 and a bootstrapped p-value of 0.001 when adding the local mean-reverting variable to the base model, and -0.934 with a t-statistic of -9.158 and a bootstrapped p-value of 0.001 when adding both the dummy and the local mean-reverting variables to the base model. These results appear to confirm a significantly negative relation between credit spreads and interest rates, including when the time-series behavior of interest rates is being taken into account. Under Regime II&III, our results show that the estimates are quantitatively similar to the estimates obtained under Regime I&III, suggesting the identification through heteroscedasticity approach is robust.

In Panel B, for high-yield bonds under Regime A, credit spreads' reaction to interest rates is -2.498 with a t-statistic of -3.865 and a bootstrapped p-value of 0.015 in the base model, and -2.649 with a t-statistic of -3.729 and a bootstrapped p-value of 0.025 when including the local mean-reverting variable to the base model. The relation is again similar under Regime II&III, suggesting that the estimation is valid and robust to both types of bonds and volatility regimes. It is also worth noting that high-yield bond credit spreads additionally display a higher sensitivity to interest rates than investment-grade bond credit spreads do, a result consistent with the ubiquitous risk-return tradeoff.

As a robustness check, we also perform all estimations using levels of interest rates and credit spreads. When using levels instead of their changes, we continue to observe a robust negative reaction of credit spreads on interest rates in all cases, with estimated parameters statistically significant at the 1% level.

1.3.3. Relation between Changes in Interest Rates and Credit Spreads, with Common Shocks and Business Cycle Dummy

In the bivariate structural VAR model, we assume the structural shocks to be orthogonal to interest rates and credit spreads. However, confounding macroeconomic factors can have a simultaneous influence on both interest rates and credit spreads. In this subsection, we relax the orthogonality assumption by taking a set of common shocks M_t and a business cycle dummy BC_t into account and once again empirically estimate the impact of interest rates on credit spreads. For this exercise, we select the following macroeconomic variables: Inflation Rate (INF), Unemployment Rate (UER), Industrial Productivity Index (IPI), Personal Disposable Income (PDI), Personal Consumer Expenditures (PCE), and Excess Stock Market Returns (RMRF). The common shocks are measured by the residuals of an AR (1) model fitted to each macroeconomic variable. The business cycle dummy is equal to one for recession periods and to zero for expansionary periods according to NBER business cycle dates. For comparison purposes, we adopt the same regime segregation approach as in the previous section, and present results in Table 1.4.

Table 1.4 shows that the negative relation between interest rates and credit spreads still holds when accounting for common macroeconomic shocks and the effect of business cycles. In Panel A, for investment-grade bonds, under Regime I&III the estimated α (credit spreads' reaction to interest rates) is -0.979 with a t-statistic of -12.075 and a bootstrapped p-value of 0.000 with the macroeconomic variables added to the base model, -0.973 with a t-statistic of -11.715 and a bootstrapped p-value of 0.000 when adding the business cycle dummy variable to the base model, -0.992 with a t-statistic of -12.221 and a bootstrapped p-value of 0.000 when adding both the business cycle dummy and the macroeconomic variables to the base model.

In Panel B, for high-yield bonds, under Regime I&III, the credit spreads' reaction to interest rates is -2.990 with a t-statistic of -4.046 and a bootstrapped p-value of 0.012 when the macroeconomic shock are added into the base model and -2.800 with a t-statistic of -3.259 and a

bootstrapped p-value of 0.031 when including business the cycle dummy variable to the base model, -3.163 with a t-statistic of -4.141 and a bootstrapped p-value of 0.009 when adding both the business cycle dummy and the macroeconomic variables to the base model. Finally, just like in Table 3, the results under Regime II&III suggest that the relation between credit spreads and interest rates is quantitatively similar to the relation estimated under Regime I&III. The presence of common macroeconomic shocks and the effect of business cycles thus do not appear to significantly affect the relation between interest spreads and credit spreads.

1.4 Explanations for the Negative Relation, Reexamined

1.4.1 The Callability Feature

Given the economic and statistically significant negative relation between credit spreads and interest rates, we next begin to investigate its possible drivers. Duffee (1998) reports that the negative relation between interest rates and credit spreads is weakened when the callability option is excluded from the corporate bond pool, and argues that the callability feature is a non-negligible concern in the negative relation due to the fact that corporate bond indices usually contain a large portion of callable bonds. Jacoby, Liao and Batten (2007) use a Canadian bond index devoid of any callability characteristics, and find no significant relation between interest rates and corporate bond credit spreads. Our additional findings that the impact of interest rates on high-yield bond credit spreads is two to three times larger than on investment-grade bond credit spreads seems consistent with the fact that callable bonds make up less than 1% of the investment-grade bonds pool while they make up about 70% of the high-yield bonds pool (see Aneiro, 2014). Our conclusions thus at first appear to be in line with the results in Jacoby, Liao and Batten (2007). However, King [2002] finds that the call option value constitutes only around 2 percent of the par value of the average callable bond, implying that given the small contribution of the callability feature to the bond value,

it would seem unlikely that this aspect of the bond would alone be responsible for the negative correlation between credit spreads and interest rates.

To further explore whether the callability embedded in bond index might be a possible explanation for the large sensitivity of credit spreads to interest rates, we conduct estimations and tests on both the Bank of America - Merrill Lynch aggregate corporate bond index and the aggregate corporate bond index that excludes Yankee and optionable bonds, and compare the results. The sample of Bank of America – Merrill Lynch data extends from January 1995 to December 2014. We adopt the same regime separation methodology as in the previous sections, and report the results in Table 1.5.

Table 1.5 shows that, when using a corporate bond index that excludes Yankee and optionable bonds, credit spreads still respond negatively to interest rates. Under Regime I&III, the reaction of credit spreads to interest rates for the aggregate corporate bond index (with options) is -1.941 with a bootstrapped p-value of 0.139, while the reaction of credit spreads to interest rates for the aggregate corporate bond index that excludes Yankee bonds and optionable bonds is -1.921 with a bootstrapped p-value of 0.105. Under Regime B, the results are quantitatively similar, with all estimates statistically significant at the 1% level. Our findings are thus consistent with King's (2002) since the difference between option-embedded and option-free bonds is minimal: the parameter percentage difference between the corporate bond index with and without callable bonds across regimes is actually an average value of 2 percent. We can therefore conclude that a possible callability feature would not appear to affect the relation between credit spreads and interest rates much.

1.4.2 Business Cycles

Now that the callability of corporate bonds has been excluded as a possible culprit for the negative response of credit spreads to interest rates, we reexamine an alternative explanation and

focus on the negative relation between interest rates and credit spreads from a business cycles point of view. Davies (2008) uses a regime-switching model to capture business cycle transitions and shows that the negative relationship exists independently across different inflationary environments. Delianedis and Geske (2001) conclude that credit risk and credit spreads are not primarily attributable to default and recovery risk but are mainly due to tax, liquidity, and market risk factors. Wu and Zhang (2008) identify fundamental risk dimensions such as inflation, real output growth, and financial market volatility; they show that positive shocks to real output growth increase Treasury yields but narrow credit spreads at low credit-rating classes, thereby generating negative correlations between interest rates and credit spreads. Nielsen (2012) develops a structural credit-risk model that includes both business cycles and jump risk to show how the interaction between these two factors can explain business cycles variation in short- and medium-term credit spreads. In another attempt to link credit spreads to business cycles, Gilchrist and Zakrajsek (2012) decompose the credit spread into an expected default component and an excess bond premium, and show that an increase in the latter causes a contraction in the credit supply and a deterioration of macroeconomic conditions. Lastly, Barnea and Menashe (2014) extend Gilchrist and Zakrajsek (2012)'s work by applying their methodology to the banking sector and reach similar conclusions.

In a recession, the Federal Reserve usually gradually decreases the federal funds rate as an attempt to stimulate investments (until things turn around). Simultaneously, the worsening of the economy increases the risk of a firm through several mechanisms. From an operational point of view, sales conditions in a recession get worse due to the lower demand for consumption, and uncertainty increases. From a financial point of view, the poor economic environment makes it more difficult for the firm to obtain external financing and raises financing costs. Therefore, the increase in the firm's risk leads to a widening of the firm's corporate bonds' credit spreads. Consequently, when interest rates are decreasing, one can on average expect credit spreads to be on the rise. Conversely, in a period of economic expansion, the Federal Reserve tends to gradually

increase the federal funds rate as a way of keeping inflation under control and preventing the economy from overheating. At the same time, this economic growth progressively leads to a decrease in the firm's risk both from an operational point of view (higher sales and lower uncertainty) and through decreased financing risk and costs, ultimately resulting in a narrowing of its corporate bonds' credit spreads. Therefore, when interest rates are increasing, one should on average expect credit spreads to be on the decline.

We first use the business cycle dates reported by the National Bureau of Economic Research (NBER) to investigate the general directions of interest rates and credit spreads during contraction and expansion periods. We report the average changes in interest rates and credit spreads for the overall sample, as well as for separate periods of contractions and expansions for investment-grade and high-yield bonds in Table 1.6.

In the full sample, for both investment-grade and high-yield bonds, average changes in interest rates and credit spreads are not statistically significantly different from zero. However, during periods of economic contractions, the average change in interest rates is statistically significantly negative and the average change in credit spreads is statistically significantly positive. Conversely, during periods of economic expansion, the average change in interest rates is positive and the average change in credit spreads is negative. For investment-grade bonds, all results are statistically significant at the 5% level. For high-yield bonds, although the signs of the estimated coefficients are in line with our business cycle proposition, the 5% significance level is not met. This might be explained by the fact that a junk bond already displaying a high credit spread will most likely not see its credit spread increase tremendously even in recessionary periods since its credit premium is already high. Conversely, the same high-yield bond will not see its credit spread decrease tremendously even during expansionary periods since the firm remains a somewhat default-prone one in general.

Overall, the results found in Table 1.7 appear to support the idea that the negative relationship between interest rates and credit spreads could simply be due to their timing with respect to business cycles. However, mere synchronicity does not necessarily indicate that business cycles actually cause the negative relation. We further investigate whether the negative relationship originates from the business climate using a two-step approach that considers both macroeconomic variables and NBER business cycle dates. In a first step, we regress changes in credit spreads and interest rates on a set of macroeconomic variables and a business cycle dummy as described by the following two equations:

$$\Delta CS_t = const. + b_1 M_t + b_2 BC_t + \varepsilon_{cs} \tag{1.15}$$

$$\Delta TB_t = const. + b_1 M_t + b_2 BC_t + \varepsilon_{tb} \tag{1.16}$$

where M_t represents the six macroeconomic variables previously defined and where BC_t is a business cycle dummy equal to one or zero for recession and expansion periods.

Equations (1.15) and (1.16) are run alternatively with only the macroeconomic variables, only the business cycle dummy, or both. From these we are then able to back out two sets of residuals ε_{cs} and ε_{tb} that can now be seen as interest rate and credit spread changes devoid of macroeconomic interferences, business cycles effects, or both. In a second step, we estimate the contemporaneous relation between ε_{cs} and ε_{tb} by means of the identification through heteroskedasticity methodology. In a nutshell, equations (1.1) through (1.8) are revisited where ΔCS_t and ΔTB_t are now replaced with ε_{cs} and ε_{tb}. For comparison purposes, we adopt the same regime segregation approach as in the previous sections, and present results in Table 1.7.

Focusing on regime I&III, when the six macroeconomic variables are used in equations (1.15) and (1.16) alone, for investment-grade bonds (Panel A) the estimated α (credit spreads' reaction to interest rates) is -1.007 with a t-statistic of -13.045 and a bootstrapped p-value of 0.000, while for high-yield bonds (Panel B) the estimated α is -2.928 with a t-statistic of -4.022 and a bootstrapped p-value of 0.012. With only the business cycle dummy present in equations (1.15) and (1.16), the

estimated α for investment-grade bonds is -0.942 with a t-statistic of -12.923 and a bootstrapped p-value of 0.000, while for high-yield bonds it is -2.835 with a t-statistic of -3.130 and a bootstrapped p-value of 0.034. Finally, when macroeconomic variables and business cycle effects are all removed, the negative response of credit spreads to interest rates does not vary much. For investment-grade bonds the estimated α is -0.994 with a t-statistic of -13.090 and a bootstrapped p-value of 0.002, while for high-yield bonds the credit spreads' reaction to interest rates is -3.153 with a t-statistic of -4.159 and a bootstrapped p-value of 0.006. Additionally, just like in Table 1.3, the results under Regime II&III suggest that the relation between credit spreads and interest rates is quantitatively similar to the relation estimated under Regime I&III. These findings thus lead us to conclude that common macroeconomic shocks and business cycles do not appear to explain the negative relation between interest spreads and credit spreads.

1.5 Conclusion

The relationship between interest rates and credit spreads is of paramount importance to portfolio and risk managers since both the size and the direction of credit spreads' reactions to changes in Treasury yields determine the sign and magnitude of subsequent corporate bond price movements. In this paper, we reexamine the relation between government rates and corporate credit spreads by applying Rigobon's (2003) method of identification through heteroskedasticity to the issue. We find significant and robust evidence of a negative reaction of credit spreads to interest rates, in line with Merton's (1974) structural model predictions. We also show that our results are robust to a variety of factors related to the time-series properties of interest rates such as the presence of permanent (or near-permanent) shocks and their low speed of mean reversion, varying volatility regimes, different corporate bond ratings, and various macroeconomic variables affecting the economy as a whole.

Additionally, by testing the relation using a corporate bond index devoid of callable bonds, we are also able to rule out the callability feature of corporate bonds as the main factor behind the negative correlation between Treasury rates and corporate credit spreads. Lastly, we show that although business cycles at first appear to be the likely culprit for the relation, macroeconomic and business conditions are in fact ruled out as a possible explanation. We empirically demonstrate that the response of credit spreads to interest rates remains statistically significantly negative even when the effects of business cycles and a set of macroeconomic variables are removed from the credit spreads and Treasury yields time series.

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Appendix

The price of a bond *B* yielding a rate *y* and paying *n* coupons C_i at various times t_i can be expressed with continuous compounding as

$$B = \sum_{i=1}^{n} c_i e^{-yt_i} \qquad \text{(A1.1)}$$

The corresponding duration *D* of the bond is

$$D = \sum_{i=1}^{n} t_i \frac{c_i e^{-yt_i}}{B} \qquad \text{(A1.2)}$$

If we express the bond yield *y* as the sum of the risk-free rate *r* and a credit spread *cs(r)*, the bond price can instead be written as

$$B = \sum_{i=1}^{n} c_i e^{-(r+cs(r))t_i} \qquad \text{(A1.3)}$$

Differentiating the bond price with respect to the risk-free rate *r* rather than to the yield *y* gives

$$\frac{dB}{dr} = -\sum_{i=1}^{n} c_i t_i \left(1 + \frac{d[cs(r)]}{dr}\right) e^{-yt_i} \tag{A1.4}$$

Combining equations (A2) and (A4), it is straightforward to show that

$$\frac{dB}{dr} = -DB\left(1 + \frac{d[cs(r)]}{dr}\right) \tag{A1.5}$$

Equation (A1.5) implies that there are three theoretical possible cases.

First, if credit spreads respond positively to an increase in interest rates, the derivative term inside the parentheses in (A1.5) will be positive and the term in parentheses will be higher than one. The bond yield will thus increase by more than the increase in the risk-free rate since both of its components go up, and the bond price will therefore fall by more than it would if credit spreads and interest rates were uncorrelated.

Second, if credit spreads on average do not respond in either direction to an increase in interest rates, the derivative term inside the parentheses in (A1.5) will be equal to zero and the term in parentheses will be equal to one. Equation (A1.5) then collapses to the traditional relation between bond price changes and duration. The bond yield will increase by exactly the same amount as the risk-free rate since the credit spread or risk premium is unaffected, and the bond price will therefore fall accordingly.

Finally, if credit spreads respond negatively to an increase in interest rates, the derivative term inside the parentheses in (A1.5) will be negative and of the following values or range:

Strictly between 0 and -1 and the term in parentheses will still be positive. The bond yield will thus increase by less than the increase in the risk-free rate since one of its components (the risk-free rate) goes up while the other (the credit spread) goes down by a lesser amount. The bond price will therefore fall by less than it would if credit spreads and interest rates were uncorrelated.

Equal to -1 and the term in parentheses will be equal to zero. The bond yield will thus stay the same since one of its components (the risk-free rate) goes up while the other (the credit spread) goes down by the exact same amount. The bond price will therefore remain the same.

Strictly less than -1 and the term in parentheses will be negative. The bond yield will thus decrease since one of its components (the risk-free rate) goes up while the other (the credit spread) goes down by more than the former. The bond price will therefore go up.

Tables

Table 1.1 Descriptive Statistics

Table 1.1 summarizes monthly statistics for levels of, and changes in, Treasury Bill rates (TB), credit spreads for investment-grade bonds (CS_IG), credit spreads for high-yield bonds (CS_HY), inflation rate (INF), Fama-French excess market returns (RMRF), unemployment rate (UER), industrial productivity Index (IPI), personal disposable income (PDI) and personal consumer expenditures (PCE). The Δ symbol represents the first difference. The credit spreads are measured as yields of the corporate bond index minus the 3-month Treasury bill rate. Inflation (INF), extracted from the St. Louis FED, is the one-month percentage change in CPI. The excess return on the market (RMRF), retrieved from the Kenneth R. French – Data Library, is the value-weighted return on the CRSP index minus the one-month Treasury bill rate. Unemployment rate (UER), industrial productivity Index (IPI), personal disposable income (PDI) and personal consumer expenditure (PCE) are the one-month percentage changes for each variable, also obtained from the St. Louis FED. All variables are from January 1973 to December 2014, except CSHY available from January 1987 to December 2014 only.

Variable	Mean	Sigma	Min	Max	AR (1)
TB (%)	5.052	3.440	0.010	16.300	0.992
ΔTB (%)	-0.010	0.484	-4.620	2.610	0.088
CS_IG (%)	2.826	1.412	-2.160	8.380	0.944
ΔCS_IG (%)	0.002	0.472	-3.110	3.860	0.327
CS_HY (%)	7.102	2.795	2.420	21.640	0.969
ΔCS_HY (%)	-0.001	0.693	-2.940	5.220	0.346
INF (% change)	0.341	0.344	-1.771	1.810	0.642
RMRF (%)	0.541	4.596	-23.000	16.010	0.069
UER (%)	6.463	1.572	3.800	10.800	0.993
IPI (% change)	0.180	0.727	-4.208	2.089	0.346
PDI (% change)	0.525	0.792	-5.845	6.163	-0.156
PCE (% change)	0.540	0.546	-2.022	2.770	-0.062

**AR (1) is the estimated coefficient of an AR (1) process with a constant.*

Table 1.2 Unit Root Tests for Levels of Interest Rates and Credit Spreads

Table 1.2 reports the results from the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for both interest rates (TB) and credit spreads (CS_IG and CS_HY for investment-grade and high-yield bonds respectively), along with test statistics and significance levels. The ADF and PP tests include a constant, a linear trend and three lags.

Variable	ADF	PP
TB	-3.165*	-3.285*
CS_IG	-4.080***	-4.116***
CS_HY	-3.378*	-2.856

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively. For the ADF and PP tests, the critical values at the 1%, 5% and 10% significance levels are -3.981, -3.421 and -3.13 respectively.*

Table 1.3 Relationship between Changes in Interest Rates and Credit Spreads in Two Regimes without Common Macroeconomic Shocks

Table 1.3 reports regression estimates of the sensitivity of changes in monthly credit spreads (ΔCS_t) to changes in interest rates (ΔTB_t) for the January 1973 to December 2014 period for two regimes and four different cases, with t-statistics displayed in parentheses and with the "L" index representing up to three lags. The bootstrapped P-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime II&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. Case 1 is the base model where the residuals $\alpha\mu_t + \nu_t$ and $+\mu_t + \beta\nu_t$ in the VAR system ($\Delta CS_t = (\alpha\ \Delta TB_L + \theta\ \Delta CS_L + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L + \lambda\ \Delta TB_L + \mu_t + \beta\nu_t)/(1-\alpha\beta)$) are estimated without any extra variable(s). Case 2 is the model where the residuals in the VAR system ($\Delta CS_t = (\alpha\ \Delta TB_L + \theta\ \Delta CS_L + \phi_1 D_t + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L + \lambda\ \Delta TB_L + \psi_1 D_t + \mu_t + \beta\nu_t)/(1-\alpha\beta)$) are estimated with a dummy variable D_t set to 1 between January 1973 and August 1981 and set to zero between September 1981 and December 2014. Case 3 is the model where the residuals in the VAR system ($\Delta CS_t = (\alpha\ \Delta TB_L + \theta\ \Delta CS_L + \phi_2[TB_t - K_t] + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L + \lambda\ \Delta TB_L + \psi_2[TB_t - K_t] + \mu_t + \beta\nu_t))/(1-\alpha\beta)$) are estimated with a mean-reverting level K_t of interest rates calculated as a 5-year moving average. Case 4 is the model where the residuals in the VAR system ($\Delta CS_t = (\alpha\ \Delta TB_L + \theta\ \Delta CS_L + \phi_1 D_t + \phi_2[TB_t - K_t] + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L + \lambda\ \Delta TB_L + \psi_1 D_t + \psi_2[TB_t - K_t] + \mu_t + \beta\nu_t)/(1-\alpha\beta)$) are estimated with both a dummy D_t and a mean-reverting level K_t. Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
Base model	-0.950***	-0.891***
	(-9.716)	(-9.206)
	[0.000]	[0.004]
With dummy (D)	-0.944***	-0.900***
	(-9.461)	(-8.956)
	[0.001]	[0.002]
With mean-reverting variable	-0.935***	-0.891***
$[TB_t - K_t]$	(-9.168)	(-8.573)
	[0.001]	[0.009]
With dummy (D) &	-0.934***	-0.898***
mean-reverting variable	(-9.158)	(-8.590)
$[TB_t - K_t]$	[0.001]	[0.009]
Panel B: High-yield bonds		
Base model	-2.498***	-2.908***
	(-3.865)	(-4.765)
	[0.015]	[0.003]
With mean-reverting variable	-2.649***	-3.648***
$[TB_t - K_t]$	(-3.729)	(-4.217)
	[0.025]	[0.008]

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Table 1.4 Relationship between Changes in Interest Rates and Credit Spreads in Two Regimes with Common Macroeconomic Shocks

Table 1.4 reports regression estimates of the sensitivity of monthly credit spreads (ΔCS_t) to interest rates (ΔTB_t) for the January 1973 to December 2014 period for two regimes and four different cases, when including M_t macroeconomic shocks obtained as residuals of AR (1) processes fitted to INFt, RMRFt, UERt, IPIt, PDIt and PCEt and business cycle dummy(BC), with t-statistics displayed in parentheses and with the "L" index representing up to three lags. The bootstrapped P-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime II&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. Case 1 is the model where the residuals $(\alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $(\mu_t+\beta\nu_t)/(1-\alpha\beta)$ in the VAR system ($\Delta CS_t = (\alpha\ \Delta TB_L+\theta\ \Delta CS_L + \gamma F_t + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L+\lambda\ \Delta TB_L + \Gamma M_t + \mu_t+\beta\nu_t)/(1-\alpha\beta)$) are estimated with macroeconomic variable(s). Case 2 is the model where the residuals in the VAR system ($\Delta CS_t = \alpha\ \Delta TB_L+\theta\ \Delta CS_L + \phi_1 BC_t + \gamma M_t + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L+\lambda\ \Delta TB_L + \psi_1 BC_t + \Gamma M_t + \mu_t+\beta\nu_t)/(1-\alpha\beta)$) are estimated with a dummy variable BC_t set to 1 for the NBER recession dates and set to zero for others. Case 3 is the model where the residuals in the VAR system ($\Delta CS_t = (\alpha\ \Delta TB_L+\theta\ \Delta CS_L + \phi_1 BC_t + \gamma M_t + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and $\Delta TB_t = (\beta\ \Delta CS_L+\lambda\ \Delta TB_L + \psi_1 BC_t + \gamma M_t + \mu_t+\beta\nu_t)/(1-\alpha\beta)$) are estimated with both a business cycle dummy BC_t and macroeconomic shocks M_t. Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
Macroeconomic variables (M)	-0.979***	-0.940***
	(-12.075)	(-11.303)
	[0.000]	[0.001]
Business cycle dummy (BC)	-0.973***	-0.986***
	(-11.715)	(-10.485)
	[0.000]	[0.001]
Macroeconomic variables (M) & business cycle Dummy (BC)	-0.992***	-0.952***
	(-12.221)	(-11.443)
	[0.000]	[0.001]
Panel B: High-yield bonds		
Macroeconomic variables (M)	-2.990***	-3.297***
	(-4.046)	(-4.591)
	[0.012]	[0.004]
Business cycle dummy (BC)	-2.800***	-3.356***
	(-3.259)	(-3.364)
	[0.031]	[0.022]
Macroeconomic variables (M) & business cycle dummy (BC)	-3.163***	-3.377***
	(-4.141)	(-4.501)
	[0.009]	[0.002]

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Table 1.5 Relationship between Changes in Interest Rates and Credit Spreads in Two Regimes for Aggregate Corporate Bond Indices with and without Options

Table 1.5 reports regression estimates of the sensitivity of changes in monthly credit spreads (ΔCS_t) to changes in interest rates (ΔTB_t) for the January 1995 to December 2014 period for two regimes and the base case for both the Aggregate Corporate Bond Index and the Corporate Bond Index that excludes Yankee and optionable bonds, with t-statistics displayed in parentheses and with the "L" index representing up to two lags. The bootstrapped P-values are reported in brackets below the t-statistics. In regime A, shocks to interest rates and credit spreads are either average or significantly positive, while in regime B they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. The base case is the model where the residuals ν_t and μ_t in the VAR system ($\Delta CS_t = (\alpha\, \Delta TB_L + \theta\, \Delta CS_L + \alpha\mu_t + \nu_t)/(1-\alpha\beta)$ and ($TB_t = \beta\, \Delta CS_L + \lambda\, \Delta TB_L + \mu_t + \beta\nu_t)/(1-\alpha\beta)$) are estimated without any extra variable(s).

	α (regime I&III)	α (regime II&III)
Corporate bond index	-1.941***	-1.567***
	(-5.007)	(-5.200)
	[0.139]	[0.103]
Corporate bond index without options	-1.921***	-1.545***
	(-5.121)	(-5.190)
	[0.105]	[0.096]

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Table 1.6 Interest Rate and Credit Spread Movements in Relation to Business Cycles

Table 1.6 reports the average changes in interest rates and credit spreads for periods of expansions and contractions as defined by the NBER business cycle dates. The investment-grade bond index sample period extends from January 1973 to December 2014 while the high-yield bond index sample period stretches from January 1987 to December 2014. The t-statistics are reported below each average value.

	No. of observations	Mean
ΔTB (overall)	503	-0.011
		(-0.496)
ΔCS_IG (overall)	503	0.002
		(0.094)
ΔTB (contraction)	78	-0.260**
		(-2.519)
ΔTB (expansion)	425	0.035**
		(2.154)
ΔCS_IG (contraction)	78	0.239***
		(2.670)
ΔCS_IG (expansion)	425	-0.041**
		(-2.294)
ΔCS_HY (contraction)	37	0.280
		(1.030)
ΔCS_HY (expansion)	298	-0.035
		(-1.374)

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Table 1.7 Relationship between Changes in Interest Rates and Credit Spreads in Two Regimes Free of Macroeconomic or Business Cycles Effects

Table 1.7 reports regression estimates of the sensitivity of monthly credit spreads (ε_{cs}) to interest rates (ε_{tb}) for the January 1973 to December 2014 period for two regimes and three different cases, when controlling for M_t macroeconomic shocks obtained as residuals of AR (1) processes fitted to INFt, RMRFt, UERt, IPIt, PDIt and PCEt and for a business cycle dummy (BC), with t-statistics displayed in parentheses and with the "L" index representing up to three lags. The bootstrapped P-values are reported in brackets below the t-statistics. In regime I&III, shocks to interest rates and credit spreads are either average or significantly positive, while in regime I&III they are either average or significantly negative, as defined by their magnitude with respect to a one-sigma deviation from the mean. Case 1 is the base model where the residuals ε_{cs} and ε_{tb} are estimated using the macroeconomic variables M_t. Case 2 is the model where the residuals ε_{cs} and ε_{tb} are estimated with a dummy variable D_t set to 1 for the NBER recession dates and set to zero for others. Case 3 is the model where the residuals ε_{cs} and ε_{tb} are estimated with both a business cycle dummy D_t and macroeconomic shocks M_t. Panel A reports the results for investment-grade bonds, while panel B reports the results for high-yield bonds.

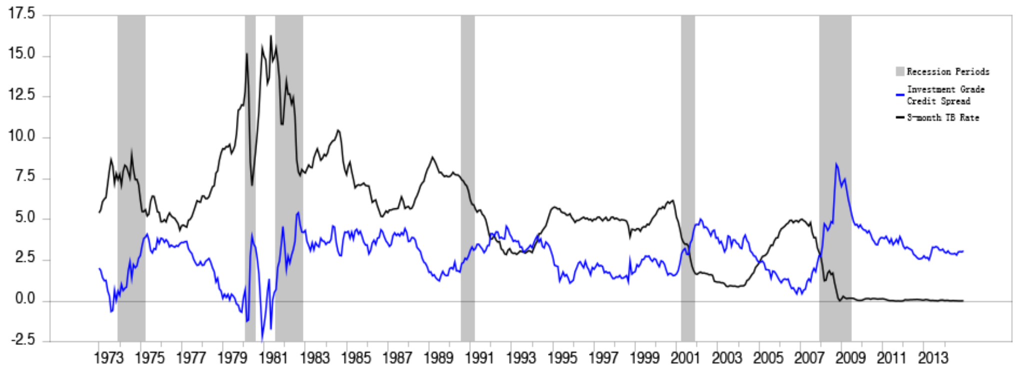
	α (regime I&III)	α (regime II&III)
Panel A: Investment-grade bonds		
Macroeconomic variables (M)	-1.007***	-1.025***
	(-13.045)	(-12.445)
	[0.000]	[0.002]
Business cycle dummy (BC)	-0.942***	-1.012***
	(-12.923)	(-11.610)
	[0.000]	[0.003]
Macroeconomic variables (M)	-0.994***	-0.995***
& business cycle dummy (BC)	(-13.090)	(-12.275)
	[0.002]	[0.001]
Panel B: High-yield bonds		
Macroeconomic variables (M)	-2.928***	-3.051***
	(-4.022)	(-4.785)
	[0.012]	[0.004]
Business cycle dummy (BC)	-2.835***	-3.397***
	-3.130	(-3.244)
	[0.034]	[0.021]
Macroeconomic variables (M)	-3.153***	-3.385***
& business cycle dummy (BC)	(-4.159)	(-4.465)
	[0.006]	[0.004]

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Figures

1.1 Three-month Treasury-bill Rates and Investment-Grade Credit Spreads from 1973.1 to 2014.12

Figure 1 plots 3-month Treasury bill rates and investment-grade credit spreads from January 1973 to December 2014. The rates are expressed in percent and reported at a monthly frequency. The shaded areas are recession periods as defined by NBER.



CHAPTER 2 : MARKET EFFICIENCY: PRICE MOVEMENT TO INTRINSIC VALUE IN COMMERCIAL REAL ESTATE

2.1 Introduction

Intrinsic value is a fundamental tenet in the literature. An investment has a base or true value based on future cash flows and the closer the asset's actual price is to this value the more efficient the market for the asset. The market should be continually moving the price of a stock toward its intrinsic value when information comes available (Fama (1965), and many others). Price should reflect intrinsic value and it as argued that in the most efficient markets intrinsic value and price are equivalent.[5]. The movement of price due to changes in intrinsic value requires market makers to formulate estimates of intrinsic value relative to price making intrinsic value a shadow value with price moving subsequently. The difficulty in assessing intrinsic value and price empirically is related to the private component inherent to intrinsic value and the unknown intrinsic value estimates formulated by investors. The price of an asset is often readily available while its intrinsic value is implied, unknown or subject to debate or challenge

There is a substantial literature related to intrinsic value including how price may deviate from intrinsic value. Fama (1995) notes that in an efficient market price and intrinsic value should be approximate. Lee, Myers and Swaminathan (1999) recognize the difficulty in estimating intrinsic value and use various measures to test the price to intrinsic value relation. While the intrinsic value construct is fundamental to many literature streams, including the derivation of value, under/overvalued stocks, mergers and many other market mechanisms, difficulty in creating systematic proxies or estimates of intrinsic value make it difficult to validate the most essential

[5] This is in a practical application. But, we can also note that when one simply assumes that price is the closest proximate to intrinsic value (even in cases when the market is dysfunctional with few arms-length transactions), one can have many mark-to-market and valuation issues. This is more readily the case for alternative assets. This was apparent during the financial crisis from 2008 to 2009. It remains a very relevant issue for policy makers and practitioners.

claim associated with efficient asset pricing which is that the asset's market price moves toward its intrinsic value.[6] A large part of the inability to empirically evaluate the intrinsic value construct is the use of accounting terms and measures versus the forward looking cash flow focus common to the finance literature.

For stocks, rational finance theory indicates that stock prices should not deviate substantially from intrinsic value. Since intrinsic value is not readily observable, researchers in the equities markets have used accounting proxies such as dividends, earnings and cash flow to estimate intrinsic value using some type of time value model that is forward looking. Such formulations are not necessarily accurate as they are assumption and modeling dependent which makes assessment of variation in price and intrinsic value difficult. In addition, they do not carry financial or investment weight since the estimates are not directly related to actual returns, asset allocations and performance monitoring. Fortunately, data from commercial real estate markets allows us to bridge the gap between asset price and intrinsic value by providing a substantially more meaningful and practiced estimation of inherent value. The data series we use to proxy intrinsic value in commercial real estate are those that have been used by institutional investors for decades and are the basis for trillions of dollars in investment over time.[7]

The commercial real estate market provides a unique opportunity to test the relations between intrinsic value and price. Because transaction volume historically has been relatively limited and variation in individual real estate assets may create greater single asset heterogeneity than stocks, institutional investors have been dependent on value indices derived from appraised (judgment) values. The longest running real estate benchmark used by institutional investors in the United States is from the National Council of Real Estate Investment Fiduciaries (NCREIF). NCREIF's

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[6] Of course, the time required to move price to value is also an area of investigation.

[7] These are "practiced" as they are used to calculate real returns used to allocate and disburse real cash by institutional investors, while concurrently meeting required statutory reporting standards.

appraisal based property index (NPI) dates from the 1970s and 1980s when real estate was in its infancy as an asset class.[8] The index is based on the systematic valuation or appraisal of the real property assets that make up the index. We postulate that the NPI is a general proxy for the intrinsic value of the underlying real estate. The index represents the collective knowledge of sophisticated valuers/analysts who typically use standard discounted cash flow techniques. Appraisal formulation is forward looking and focused on cash flows. Practical support for our use comes from the institutional real estate investment community who have relied on this index in allocating billions and trading trillions of dollars in the real estate sector.[9]

Subsequent to the NPI, NCREIF developed a transaction based (price) index (TBI) to track real estate returns. This index is generated from transactions and actual prices and dates to the 1990s. The creation of this index creates a natural test of the relations between intrinsic value and market price. While we are cognizant of the limitations in both types of indices and recognize that price discovery is more difficult in commercial real estate (Geltner, MacGregor and Schwann (2003)), the individual construction technique for each index allows for the empirical assessment of whether asset prices move toward intrinsic value. It is recognized that prices can deviate from intrinsic value and that the adjustment process may take time. Nevertheless, we can assess whether price movement is systematic toward intrinsic value as is a necessary condition for efficient markets.

Statistically significant results from our cointegrating models suggesting that the transaction based index deviates from the appraisal (judgment) index in the short run, but converges back to the equilibrium state of the TBI and NPI system. In further tests, the cointegrating residuals among the TBI, NPI and REIT indices predict the one period ahead TBI return. Again, the results are statistically significant. In particular, the TBI is the only series that is making adjustment to bring

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[8] The NPI was first published in 1977.

[9] See www.ncreif.org for an outline of development of the institutional market for real estate.

this system back to its steady state. Finally, the explanatory power of the next quarter transaction based index is compared using the cointegrating residual of TBI and ABI with the cointegrating residual of TBI, ABI and REITs. With the REIT market information, the prediction power of next period transaction index increases, but these two cointegrating residuals are sharing common information. In summary, we show the transaction index return is predictable with convergence to intrinsic value as proxied by the appraisal return series.

In the broader context, the results support the fundamental role played by intrinsic value in asset pricing. While price may deviate from intrinsic value, the market is sufficiently efficient so that it is intrinsic value that sets the long-term returns. Our results evidence the ability of market participants to recognize price deviations from value with current and subsequent movement of price to value. The movements are not random. The natural test provided, using sophisticated valuer/appraiser/analyst estimates, based on future cash flows, of intrinsic value, tie theory to market mechanisms and overcomes difficulty in the estimation of intrinsic value. While there may be market limitations and perhaps structural issues that limit price formation, our results highlight movement of price to intrinsic value as adjudicated by knowledgeable and experienced participants. The results support the theoretical cornerstone of market efficiency with price convergence to intrinsic value.

The remainder of this paper is organized as follows. Section 2.2 provides a literature assessment. Section 2.3 describes the data used in this study. Section 2.4 describes VECM system and the in-sample forecasting empirical results. Sections 2.5 to 2.8 provide results, and Section 2.9 concludes.

2.2 Literature Review

There is a large literature on commercial real estate return indices. While none of the studies specifically recognize the intrinsic value construct, the studies highlight the fact that the debate on the two types of series is itself based on market efficiency and whether price deviates from value.

The first group of studies is based on appraisal-based indices(ABIs) and the focus is on sources of appraisal smoothing in ABI and how to correct the appraisal smoothing bias (e.g., Blundell and Ward (1987), and Geltner (1989), (1991)). The key argument for appraisal smoothing of ABI is as follows. When appraisers use a weighted average of the contemporaneous information and historical appraisals to estimate value of commercial properties, this Bayesian updating approach can provide an optimal price discovery process at the individual property level, but may not be sufficiently forward looking. The argument is that by using judgment versus actual transaction date, the ABI returns have lower volatility and lag changes in the market. The argument comes from financial theory which argues for assumes that transaction price is the best estimate of value.

Several subsequent studies support the appraisal smoothing theory and the authors attempt to correct the appraisal bias using different approaches (e.g., Quan and Quigley (1991), Fisher and Geltner (2000), Clayton et al. (2001), Fu (2002) and Childs et al. (2002)). While a body of the literature presents findings consistent with the appraisal smoothing theory, other researchers argue that the appraisal smoothing may not be a serious issue. For instance, Lai and Wang (1998) point out many papers started with an assumption that appraisal smoothing exists and argue that appraisal based index actually increases commercial property return volatility instead of reducing it. Bond and Hwang (2007) explore three issues in the appraisal-based index together (i.e., smoothing, nonsynchronous appraisal and cross-sectional aggregation). They find that appraisal smoothing is much less than claimed in the previous studies. More recently, Cheng, Lin and Liu (2011) examine heterogeneity in appraiser behavior and show how it influences the appraisal smoothing theory. Their findings suggest that the appraisal smoothing argument is valid only if all appraisers choose the same smoothing technique. The conclusion is that the appraisal-based index may not suffer any significant ‘‘smoothing’’ bias, and the appraisal smoothing theory may exaggerate the effect of appraisal smoothing. In short, the appraisal related studies are to acknowledge deviations from price and value in commercial real estate with argument over validation.

Another approach to establish a reliable commercial property return index is to construct transaction based indices based on transaction price data. However, transaction based indices have their own problems. For example, Haurin (2005) claims that transaction based indices likely suffer from sample selectivity bias. Specifically, since only a small portion of the commercial properties are sold during a particular time period, it is possible that transacted commercial properties systematically differ from those not transacted. Thus, transacted properties are not representative of the stock of commercial properties and the transaction based index is biased when measuring commercial property market performance. Other limitations related to issues such as liquidity (Fisher et al. (2003) again highlight more concerns.

Besides the research on appraisal based and transaction based indices, there is also a relevant strand of literature that focuses on the relationship between securitized real estate returns and returns in the private real estate market (e.g., see Chau et al. (2001) for a review). Geltner, MacGregor, and Schwann (2003) point out, the public and private real estate returns should be co-integrated, as they are essentially based on the same assets. While transaction costs and information costs may make two return series differ from time to time, arbitrage activities will not allow the returns between the two markets to deviate too far from the fundamental values. A few studies document a Granger causality between the two markets, with securitized real estate returns leading private real estate return. For example, a recent study (Hoesli, Oikarinen and Serrano (2015)) finds that REIT returns lead private real estate returns in office, retail, and apartment sectors, but not in the industrial sector. They attribute the findings to the slow reaction of private market returns to shocks in REIT returns and also to the risk premium and economic sentiment.

The existing literature suggests that the commercial real estate market is a unique market given trading limitations, heterogeneity and its long-term use of both appraisal and transaction based return measures. Unlike most asset markets with greater liquidity and less heterogeneity (stock and bond markets, as prime exemplars), the use of judgment (appraisal) derived measures to asses and

reward performance has been normative. This requires acceptance of the validity of the return measures since these measures have both practical and economic consequences. In the present case, and of great importance, it allows us to examine how intrinsic value and price relate in the commercial property asset markets and provides testable hypotheses related to whether the market can determine intrinsic value and whether it is intrinsic value that sets the long-term equilibrium condition.

In this paper, we argue that the appraisal based index can be a reasonable proxy for the intrinsic value of commercial real estate. The index is representative of the consensus valuation of the market by known experts using standard valuation methodologies based on property cash flows. Also, because the NPI (the primary NCREIF ABI), is the return series historically used by institutional investors to support investment in real estate and for return allocations, performance attribution, compensation, etc... with real dollars being expended, its use cannot be dismissed as just another noisy model (a critique of some prior research). ABIs are created from the knowledge and experience of licensed, sophisticated appraisers and valuers who grasp the full information of the real estate markets, including the forward-looking information. The test distinguishes the ability to determine intrinsic value and the market mechanisms that bring market price and value into equilibrium.

2.3 Data

We obtain transaction based and appraisal based index data from the NCREIF website for the period of first quarter of 1994 to the fourth quarter of 2015. REIT index return data are from Zimen REITs in the CRSP database from 1994.1 to 2014.4. The inflation rate is calculated using the CPI obtained from the Saint Louis Federal Reserve. The variables under investigation are: log (in real terms) of the transaction based index (TBI), a value weighted transaction index, log (in real terms)

of the appraisal based index (ABI), a value weighted appraisal index and log (in real terms) of the REIT index (REIT), a value weighted REIT index. The dividend yields for TBI, ABI and REIT are defined as each's income return (D_1/P_0), respectively. A summary of descriptive statistics of the variables can be found in Table 2.1. Sample mean, standard deviation and coefficient of AR (1) are reported.

2.4 Stationarity and Cointegration

Both the transaction based and appraisal based indices are measured in log real terms. The REIT index is also measured in log real terms. We use TBI and ABI to denote the transaction based index and the appraisal based index. From Table 2.2, the TBI, ABI and REIT indices do not pass the Dickey-Fuller unit root test. The tests of these series do not reject the null hypothesis that there is a unit root, which implies that the TBI, ABI and REITs indices are all non-stationary series.

For these non-stationary series, we test whether these time series are cointegrated with each other and share a common trend. The number of cointegration ranks (r) is tested with the maximum eigenvalue and trace test. For the bivariate case, the trace statistics test the null hypothesis of no cointegrating vector against the alternative of at least one cointegrating vector. For TBI and ABI, the Johansen trace test suggests the presence of a single cointegrating vector. However, the TBI and REIT indices are not cointegrated per both the Engel-Grainger test and the Johansen test. When the Johansen trace test is expanded to three variables, TBI, ABI and REIT, one cointegrating vector is found. Although the Johansen cointegration rank test suggests two cointegrating vectors, we further test the stationarity of the three suggested cointegrating residuals and find that only one is stationary, which verifies that only one cointegrating vector exists. On the basis of these cointegration results, VECM is deployed to investigating the direction of causality.

2.4.1 Bivariate Vector Error Correction Model

Focus is on the bivariate vector error correction model Y_t= $[TBI_t, ABI_t]$. In the bivariate VAR model, optimal lag 2 is selected by AIC. Therefore, we adopt Grainger VECM representation as:

$$\Delta Y_t = \upsilon + \alpha\beta' Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \varepsilon_t \quad (2.1)$$

The matrices γ_1 control the short-run dynamics of the model, while the long-run cointegration relationships are captured by the matrix Π= $\alpha\beta'$. The residuals ε_t are serially and mutually independent. The coefficient matrix Π has reduced rank $r < k$ where r is the cointegrating rank estimated by Johansen's MLE method and k is the number of endogenous variable. then there exist a k x r matrices α and β each with rank r such that $\Pi = \alpha\beta$' and β'y_t is cointegrating residual. α = $[\alpha_{TBI}, \alpha_{ABI}]$ is the adjustment parameter, measuring the amount of changes in the variables that bring the system back to long run equilibrium. By the Granger Representation Theorem, at least one of α_{TBI}, α_{TBI} must be non-zero if the Y_t is cointegrated.

From Table 2.2, the Johansen's cointegration test found rank r<=1 and the cointegrating vector β'= [-34.798, 33.634]' estimated by the maximum likelihood estimation as a (2x1) vector. The β coefficients show the long run equilibrium relationships between the transaction based and appraisal based indices. The term $\beta' Y_{t-1}$ gives last period's equilibrium error, or cointegrating residual. We use EC_TA_t to denote the estimated cointegrating residual. EC_TA_t is defined as $\beta_{TBI} * TBI_t + \beta_{ABI} * ABI_t$. The Γ coefficients show the short run changes occurring due to the prior changes in the model variables.

Table 2.3 reveals a positive long run relationship between the ABI and the TBI. This finding is as expected with the appraisal based representing intrinsic value and the transaction based index subsuming market actions that move actual transactions closer to or further from intrinsic value. The appraisal based index is an aggregation of values from experienced appraisers who have sufficient information to understand and assess intrinsic property values. When the appraisal based index increases 1%, the transaction based index increases by 1.366%. The transaction based index

is more volatile than the appraisal based index due to limits in pricing formation and execution. With regard to the short run relationship, the error correction term is statistically significant for TBI. The error correction terms are positive, as expected, signaling that the system is stable and converges back to the equilibrium after some disturbance in the system. Although there is some short-run predictability in the ABI, it is the transaction based index TBI that exhibits the error correction behavior and predictability in the long run. Therefore, the transaction based index is adaptive to match the long run equilibrium of the appraisal based index. This supports the long-term relationship between transaction price and intrinsic value. The VECM results support the required market behavior for all markets as the price moves to the intrinsic value. This is a fundamental relation in financial valuation theory which has been difficult to empirically test. In the present case, the market moves to the price that the valuation experts (appraisers) estimate as intrinsic value.

2.5 Tri-variate Vector Error Correction Model

To capture the interaction of variables TBI, ABI and REIT, we turn to the tri-variate VECM with Y_t= [$TBI_t, ABI_t, REIT_t$] in equation (2.1). The optimal VAR lag is 2 selected by AIC. The Johansen's cointegration test found rank r<=1 and the cointegrating vector β'= [-35.986, 28.953, 5.449]' is estimated by the maximum likelihood estimation as a 3x1 vector. The β coefficients show the long run equilibrium relationships between transaction based, appraisal based and REIT based indices. The term $\beta' Y_{t-1}$ is the cointegrating residual of TBI, ABI and REIT, denoted by EC_TAR_t. EC_TAR_t is defined as $\beta_{TBI} * TBI_t + \beta_{ABI} * ABI_t + \beta_{REIT} * REIT_t$.

Table 2.4 shows that there is a positive long run relationship between TBI and ABI since investors transact transaction based on their and their expert valuers' (appraisers) value judgments. This finding in consistent with the bivariate case. However, compared with the bivariate VECM, the coefficients decreased due to the inclusion of REIT related information. In the short run

relationship, the error correction term is statistically significant only for TBI. The error correction adjustment parameter α is almost doubled, which means that the speed at which EC_TAR_t converges back to the equilibrium is double the speed of EC_TA_t. Although there is some short-run predictability in the ABI, the transaction based index TBI is the only factor exhibiting error correction behavior and making adjustment back to the system equilibrium. As expected under financial theory, the transaction index deviates from its intrinsic value but adjusts back to the true value in long run. With additional REIT market information, the returning or correcting speed of transaction index is doubled compared with the appraisal index only. Once again, the tri-variate VECM results support market movement to intrinsic value.

2.6 One Period Ahead in Sample Forecasting Regressions of the Transaction Based Index Return

2.6.1 One Period Ahead Forecast of the Transaction Based Index Using EC_TA_t

To check whether the appraisal based index information can provide a better prediction of transaction based index return, we establish univariate forecasting procedures with the one period lagged transaction based index return, $\Delta\mathrm{TBI}_t$, dividend yield of the transaction based index, $\mathrm{DP}_{\mathrm{TBI}_t}$, cointegrating residuals for TBI and ABI, respectively. The specification for the univariate forecasting regression is as follows

$$Y_{t+1} = a + bX_t + \varepsilon_t \tag{2.2}$$

Univariate regressions for $Y_t = \Delta\mathrm{TBI}_t$, and $X_t = \Delta\mathrm{TBI}_t$, $\mathrm{DP}_{\mathrm{TBI}_t}$, and EC_TA_t are run. Table 2.5 presents the results of univariate regressions to predict the one period ahead transaction index return. In the sample forecast literature, autocorrelation and small sample bias have been shown to be nontrivial. In terms of the autocorrelation issue, the test statistics reported below the OLS test statistic are the asymptotic Newey-West (1987) test statistic corrected for both induced

autocorrelation and conditional heteroscedasticity. In addition, to test whether these test statistics are significant in small samples, we adopt bootstrap procedure and report the bootstrap p-values for each parameter estimate in brace. The bootstrapping procedure involves creating simulated historical data for variables and then using the simulated data to generate the parameter distribution through the same estimation method as the historical data. The bootstrapping procedure consists of following four steps. First, we start to run the one period ahead regression described in equation (2.2) and store the reduced form residuals for resampling. Parameter b can then be estimated. Second, we randomly draw from stored residuals and generate two bootstrapped series ($\widehat{Y_t}$ and $\widehat{X_t}$). In the third step, using the bootstrapped ($\widehat{Y_t}$ and $\widehat{X_t}$),we re-estimate the parameter b. The fourth step is to repeat step 2 and 3 1,000 times while storing the bootstrapped parameter estimates b for each replication. Finally, the bootstrapped P-values of parameter b are reported in last row within each estimation.

It is expected that an increase of EC_TA_t will predict a high transaction index return since the appraisal index return represents or is the intrinsic value of the transaction index return. Table 2.5 shows that only EC_TA_t has significant prediction power with regard to the transaction index return. The slope coefficients are uniformly positive 0.012, indicating that the appraisal or intrinsic value index return predict the transaction index returns. The adjusted R square from the regressions are 10.3%, indicating that EC_TA_t is able to explain a substantial portion of the one period ahead transaction index returns. The Newey-West test statistic and bootstrapped p value support the significance. Serial correlation and small sample bias are not severe problems in these forecasts. Furthermore, lagged transaction index returns $\Delta\mathrm{TBI}_t$ and transaction index dividend yield $\mathrm{DP}_{\mathrm{TBI}_t}$contribute little predictive power for the transaction index return.

Even though the slope coefficient for these two variables have the right signs, the coefficients are not statistically significant and the R-squares are low. We also report multivariate forecasting

regression results involving $\Delta\mathrm{TBI}_t$, $\mathrm{DP}_{\mathrm{TBI}_t}$and measures of intrinsic value EC_TA_t. Specifically, multivariate regressions of the following form are run:

$$Y_t = a + bX_t + cEC\_TA_t + \varepsilon_t \tag{2.3}$$

where X_t = $\Delta\mathrm{TBI}_t$, $\mathrm{DP}_{\mathrm{TBI}_t}$. Since EC_TA_t is correlated to some extent with $\Delta\mathrm{TBI}_t$ and $\mathrm{DP}_{\mathrm{TBI}_t}$, we want to examine whether the predictive power of EC_TA_t survives in regressions that include all these three variables. Once again, we expect the slope coefficients corresponding to each independent variable to be positive. Table 2.5 shows EC_TA_t is the only significant variable to predict the transaction index return and the coefficient is around 0.012, which is similar to the univariate estimate. The significance is consistent across three model specification. However, the other two explanatory variables, lagged transaction index return $\Delta\mathrm{TBI}_t$ and transaction index dividend yield $\mathrm{DP}_{\mathrm{TBI}_t}$, still show little predictive power. In addition, the adjusted R square does not increase in the multiple regression, indicating the forecasting does not improve with inclusion of lagged return itself and dividend yield. The findings provide robustness to the argument that transaction prices are related to the estimated intrinsic factor from the judgment based appraisal index.

2.6.2 One Period Ahead Forecast of Transaction based Index Using EC_TAR_t

REITs, an alternative investment in the real estate market, have great influence on the transaction behavior on properties. It is argued that the REIT market sends signals to the broader real estate market due to its more rapid adjusting characteristic. Therefore, the REITs return index should be not negligible when transaction index return is forecasted. EC_TAR_t, the cointegrating residual of transaction index, appraisal index and REITs index, serves as a proxy for the interaction of the transaction index, the appraisal index and the REITs index. Table 2.6 presents the forecasting results for the one period ahead transaction index return focused on EC_TAR_t. The forecasting procedures follow the same method used in the prediction of the one period head transaction index

return by EC_TA_t in Section 2.6. The Newey-West test statistic and bootstrapped p value are reported below the OLS test statistic used to correct any autocorrelation problem or look ahead bias.

Using univariate regression, the sole cointegrating residuals explain a substantial 40.1% of the variation in one period ahead transaction index return. The coefficient of EC_TAR_t is positive 0.024, double of the magnitude 0.012 for the forecasting of transaction index return using sole EC_TA_t . Moreover, the Newey–West corrected t-statistic and bootstrapped p value for this variable indicates the estimation is valid with consideration of autocorrelation and small sample problems.

To test the robustness of the estimation, we conduct multiple regressions that include variables containing the predictive power for the transaction index return. Table 2.6 shows the regression results when both the lagged dividend yield and the lagged cointegrating residuals are included in the forecasting equation. The coefficient and significance of cointegrating residual EC_TAR_t are little affected by whether the lagged value of the transaction index return and dividend yield are included in the regression as additional explanatory variables. In contrast, the forecasting power of a regression of returns on the one period lag of the transaction index return and dividend yield are quite weak. The regression including both dividend yield and cointegrating residual has more explanatory power than the univariate model with sole cointegrating residuals evidenced by the adjusted R square increase, although the dividend yield itself is not significant.

2.7 Comparison of Bivariate Forecasting and Trivariate Forecasting

Table 2.5 and Table 2.6 demonstrate that EC_TA_t and EC_TAR_t are both significant in predicting the one period ahead transaction based index return. The cointegrating residual of TBI and ABI predicts 10.3 percent of one period ahead variation in transaction index return while the cointegrating residual of TBI, ABI and REITs contributes 40.4% to the prediction in the transaction

index return. This is consistent with the economic intuition that the REITs index provides additional information to explain the transaction index return.

Table 2.7 shows the comparison of regression results of EC_TA_t and EC_TAR_t as explanatory variables together with those of EC_TA_t and EC_TAR_t as sole explanatory variable, respectively. In the multiple regression, including EC_TA_t and EC_TAR_t, the coefficient and statistical significance varies little. However, the adjusted R square increases to 46.5%, which is larger than either of the univariate regressions' adjusted R square measures, but less than the sum of adjusted R squares in the two univariate regressions. This reveals that EC_TAR_t contains information about the future transaction index return that is not included in EC_TA_t and that EC_TA_t and EC_TAR_t also share part of this information in forecasting. The results indicate that the adjustment of the transaction index return in the long run equilibrium of TBI and ABI is different from the adjustment of the transaction index return in the long run equilibrium of TBI, ABI and REITs. These two adjustments contribute relevant, but different information to predict the next period transaction index return.

We also apply long horizon forecasting to identify the long run predictive power of the cointegrating residuals, but no ability to provide long horizon forecasting is found. Therefore, we do not report the long horizon forecast results.

2.8 One Period Ahead Out of Sample Forecasting Regressions of the Transaction Based Index Return

In forecasting regressions, one problem that has to be addressed is the potential for a look ahead bias since the error correction terms of EC_TA_t and EC_TAR_t are estimated using the full sample. If the transaction index return, however, is simulated based on the error correction residuals that are not available at the time of forecasting, it will diminish its forecasting accuracy. This problem

is addressed via out of sample forecasting, which only uses the error correction residuals up to the forecasting period. The error correction residuals are re-estimated each period after the forecast is made. If the error correction residuals (EC) have low prediction power after the look ahead bias is removed, the out of sample estimations would generate high forecasting errors when estimating the parameter. The mean squared forecasting error of the restricted model, which excludes the error correction residual (EC) and that of the unrestricted model, which includes the error correction residual (EC) are compared to evaluate whether the unrestricted model nests the restricted model or the opposite. In the benchmark selection, we adopt Lettau and Ludvigson's (2001) autoregressive benchmark. We use the one period lagged transaction based index return and the constant expected returns benchmark, which includes a constant as the independent variable. Both of these two benchmark models are compared to models with the error correction residual (EC). The initial estimation period begins from the first quarter of 1994 to the fourth quarter of 1999. We then re-estimate the error correction residual (EC) by the recursive regression where forecasting models estimated with more data as forecasting moves forward in time. We also provide the results from fixed out of sample forecasting where forecasting models are estimated just once with observations from 1994 to 1999 and the same coefficient estimates used to generate all following forecasts.

To determine whether the unrestricted models that include the error correction residuals(EC) are superior to the restricted models that do not include the error correction residuals (EC), both the ENC test MSE-F tests are implemented. The ENC test, provided by Clark and McCracken(), is an encompassing forecast test. The null hypothesis is that the restricted model forecasting encompasses all the information of the unrestricted model versus the alternative that the unrestricted model provides additional information that can better forecast the transaction index return. MSE_F is the McCracken (2004) F-statistic. It tests for the equal mean squared error of the unrestricted model and restricted model. The null hypothesis is that the mean squared error from the unrestricted model equals that of the restricted model while the alternative hypothesis is that

the mean squared error is higher in the restricted model than in the unrestricted model. We compare the F-statistic with their asymptotic 95% critical values.

The Table 2.8 reports the nested out of sample forecasts of the one period ahead transaction based index return ($\Delta \mathrm{TBI}_{t+1}$) using cointegrating residuals EC_TA (the transaction based index and appraisal based index cointegrating residual) and EC_TAR (the transaction based index, appraisal based index and REITs index cointegrating residual), respectively. Panel A presents the forecasting results when the cointegrating parameters are recursively re-estimated and Panel B reports the fixed cointegrating parameters in full sample. Within the AR benchmark, whether the cointegrating residuals are re-estimated or not, the mean squared error is always lower for the unrestricted model than restricted model. MSE_u/MSE_r is less than 1 and means the unrestricted model has lower forecasting error than the restricted model. The MSE_u/MSE_r of cointegrating residuals EC_TA is close to 0.9. It implies the additional information provided by appraisal based index will improve the forecasting model only with its lagged transaction index return. Furthermore, the MSE_u/MSE_r of cointegrating residuals EC_TAR is close to 0.6, even less than 0.9, which indicates adding more REITs index information along with the appraisal index will further improve prediction of the transaction index return.

Next, for the constant benchmark, the results are similar to the AR benchmark. The cointegrating residual EC_TA provides better forecasting performance than the constant expected return forecast model, which means the appraisal based index increases the predictive power of the transaction index return. Moreover, the REITs index return increases the predictive power even more as REIT information is included. The table also presents the ENC and MSE_F and 95% critical values for comparison. For the AR benchmark model, both the ENC and MSE_F tests significantly reject the null hypothesis that the cointegrating residual EC_TA contains no information on forecasted transaction index return. Likewise, these two tests more strongly rejected the null hypothesis that the cointegrating residual EC_TAR provides no improvement in forecasting

transaction index return. The results under both the re-estimated forecasting scheme and fixed forecasting scheme are consistent. For the constant benchmark model, similar results are obtained except that only one estimation of EC_TA under the fixed scheme is marginally significant, which is consistent with Clark and McCracken's statement that the MSE_F test has less test validity than the ENC test. Therefore, using out of sample forecasts, the appraisal based index return provides more predictability of transaction based index one period ahead return than its own one period lag or constant. Furthermore, the REITs index return along with the appraisal based index return, enhance the predictability power more than just adding appraisal based index information.

2.9 Conclusion

Unique characteristics found in the commercial real estate market allow for a practical test of whether market formulated intrinsic value and deviations from intrinsic value behave as expected by theory. Empirical assessment is limited in the stock market as there is no readily identifiable proxy for an asset's or market's intrinsic value, whereas the commercial real estate market uses both an appraisal/judgment based return series as well as a transaction based return series to measure performance. The actual use of both return measures in determining the allocation of trillions of dollars in real estate investments over the last four decades allows the testing of one of the most basic tenets in investment theory: the central role of intrinsic value in the movement of asset values and the assumption that the market and asset prices move toward intrinsic value.

Using the longest running commercial real estate return series used by institutional investors provided NCREIF, the appraisal based (ABI) property index (NCREIF's NPI) dating from the 1970s, along with a relatively new transaction based (price) index (TBI), also provided by NCREIF, dating to the 1990s, we are able to discern that asset and market prices move toward intrinsic value. We are able to determine that the market uses available information to formulate intrinsic value and it is these intrinsic value formulations that move the market.

Our results show that while transaction prices and transaction based return series may stray from intrinsic value in the short-term, over the longer term, it is intrinsic value, proxied in this case by appraisal returns, that brings the market back toward equilibrium. Results from the use of various VECMs show the transaction (TBI) based return index converging to the equilibrium and the transaction based index return being predictable in the future primarily due to the intrinsic values from the ABI and cointegrating residuals that include any informational content available from REITs returns. The results strongly suggest that the asset price convergence to intrinsic value.

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Tables

Table 2.1 Data Summary Statistics

Table 2.1 summarizes quarterly statistics for the log return of transaction based index ΔTBI, the log dividend yield of transaction based index DP_TBI, the log return of appraisal based index ΔABI, the log dividend yield of appraisal based index DP_ABI, the log return of REITs index ΔREITs, the log dividend yield of REITs index DP_REITs, the demeaned cointegrating residual of transaction index and appraisal based index EC_TA and the demeaned cointegrating residual of transaction based index, appraisal based index and REITs index EC_TAR. The transaction based index and appraisal based index are extracted from NCREIF database and the REITs index are retrieved from CRSP Zimen REITs. The error correction term EC_TA is the demeaned value of $\widehat{\alpha_{tbi}} * \Delta\mathrm{TBI}_t - \widehat{\alpha_{abi}} * \Delta\mathrm{ABI}_{t-1}$.The cointegrating factors α from VECM are estimated by MLE. Variables for TBI and ABI are from the first quarter of 1994 to the fourth quarter of 2015 and variables for REITs are from the first quarter of 1994 to the fourth quarter of 2014.

Variables	Obs	Mean	Std. Error	Min	Max	AR (1)
ΔTBI	87	0.017	0.051	-0.205	0.159	-0.185
DP_TBI	88	-4.473	0.309	-5.793	-3.983	0.776
ΔABI	87	0.018	0.022	-0.089	0.063	0.718
DP_ABI	88	-4.454	0.306	-5.783	-4.021	0.800
ΔREITs	83	0.020	0.100	-0.398	0.272	0.164
DP_REITs	84	-4.187	0.252	-4.742	-3.506	0.540
EC_TA	88	0.000	1.408	-3.538	4.028	0.368
EC_TAR	84	0.000	1.384	-4.905	3.466	0.176

Table 2.2 Stationarity and Cointegration Test

Table 2.2 reports the output of the unit root test of the log transaction based index TBI, the log appraisal based index ABI and the log REITs index REITs and the cointegration test of TBI&ABI and TB&ABI&REITs. Panel A reports the Dickey-Fuller unit root test of the level and the first order difference for the log transaction based index TBI, the log appraisal based index ABI, the log REITs index REITs, respectively. The 95th percentile critical values are reported in the last column. Panel B reports the Engel Grainger cointegration test statistics and the 95th percentile critical values. Panel C reports the Johansen cointegration rank test. The lambda max tests the null hypothesis of r and the alternative of r+1 cointegrating vectors. The Lambda-trace tests the null that there are no more than r cointegrating vectors against alternative of ore than r. The unit root test of cointegrating residuals further test the stationarity of cointegrating residuals estimated by MLE. The 95th percentile critical values of lambda trace test are reported in the last column.

Panel A: Dickey-Fuller Unit Root Test

Series	Statistics	95%CV
TBI	-0.914	-2.894
ABI	-0.333	-2.894
REITs	-0.875	-2.896
ΔTBI	-11.348	-2.894
ΔABI	-3.695	-2.894
ΔREITs	-7.526	-2.896

Panel B: Engel Grainger Cointegration Test

Series	Statistics	95%CV
TBI & ABI	-4.273	-3.407
REITs & ABI	-3.166	-3.411
TBI, ABI, REITs	-5.581	-3.845

Panel C: Johansen Cointegration Rank Test

H_0	H_a	L-max	L-max 95%	Trace	Trace 95%
			TBI&ABI		
R=0	R>0	30.250	14.100	30.652	15.410
R<=1	R>1	0.402	3.840	0.402	3.840
			TBI&ABI&REITs		
R=0	R>0	40.709	20.500	64.971	29.800
R<=1	R>1	23.845	14.100	24.262	15.410
R<=2	R>2	0.417	3.840	0.4173	3.840

Table 2.3 Estimates from a Cointegrated VAR of ΔTBI_t and ΔABI_t

The table 2.3 reports the estimated coefficients from cointegrated vector autoregressions of the column variable on the row variable; t-statistics are in parentheses. Estimated coefficients that are significant at the 5-percent level are highlighted in bold face. ΔTBI is the log return of transaction based index and ΔABI is the log return of appraisal based index. The term EC_TA is the estimated error correction residual. The sample spans the first quarter of 1994 to the fourth quarter of 2015.

	Equation	
Dependent Variable	$\Delta\mathrm{TBI}_t$	$\Delta\mathrm{ABI}_t$
$\Delta\mathrm{TBI}_{t-1}$	-0.130	-0.050
	(-1.084)	(-1.071)
$\Delta\mathrm{ABI}_{t-1}$	**1.366**	**0.708**
	(6.069)	(7.996)
$\mathrm{EC\_TA}_{t-1}$	**0.018**	-0.002
	(4.161)	(-1.336)
Constant	**0.120**	-0.010
	(4.182)	(-0.847)

Table 2.4 Estimates from a Trivariate Cointegrated VAR of ΔTBI_t, ΔABI_t and $\Delta REITs_t$

The table 2.4 reports the estimated coefficients from cointegrated vector auto regressions of the column variable on the row variable; *t*-statistics are in parentheses. Estimated coefficients that are significant at the 5-percent level are highlighted in bold face. ΔTBI is the log return of transaction based index, ΔABI is the log return of appraisal based index and ΔREITs is the log return of REITs index. The term EC_TAR is the estimated error correction residual of ΔTBI, ΔABI and ΔREITs. The sample spans the first quarter of 1994 to the fourth quarter of 2015.

Dependent Variable	ΔTBI_t	ΔABI_t	ΔREITs_t
ΔTBI_{t-1}	-0.036	-0.003	-0.110
	(-0.337)	(-0.068)	(-0.373)
ΔABI_{t-1}	**0.855**	**0.701**	-0.537
	(4.064)	(7.442)	(-0.915)
ΔREITs_{t-1}	-0.074	0.022	0.252
	(-1.533)	(1.008)	(1.866)
EC_TAR_{t-1}	**0.025**	0.001	-0.009
	(6.321)	(0.296)	(-0.785)
Constant	**0.230**	0.010	-0.052
	(6.341)	(0.608)	(-0.516)

Table 2.5 One Period Ahead Forecast of ΔTBI_{t+1} related to EC_TA_t

The table 2.5 reports the output from one period ahead regressions of ΔTBI_{t+1} (transaction based index return) on ΔTBI_t (transaction based index return), DP_{TBI_t}(Dividend yield of transaction based index), EC_TA (cointegrating residual for TBI&ABI), respectively in Panel A and combinatorically in Panel B. t-statistics are in parentheses, Newey-west t-statistics are in brackets, bootstrapped p-value are in braces and adjusted R square statistics are in the last column. Estimated coefficients that are significant for OLS, Newey-west and bootstrap estimations at the 5-percent level are highlighted in bold face. The sample spans the first quarter of 1994 to the fourth quarter of 2015.

ΔTBI_{t+1}	ΔTBI_t	DP_TBI_t	EC_TA_t	$\bar{R}^2$
Panel A: Univariate Forecast				
	-0.185			0.025
	(-1.772)			
	[-1.752]			
	{0.073}			
		0.017		-0.001
		(0.948)		
		[1.523]		
		{0.356}		
			0.012	0.103
			(3.291)	
			[2.954]	
			{0.002}	
Panel B: multivariate Forecast				
	0.051		**0.013**	
	(0.367)		(2.492)	0.082
	[0.347]		[2.322]	
	{0.688}		{0.022}	
		0.015	**0.012**	0.100
		(0.894)	(3.257)	
		[1.060]	[2.915]	
		{0.562}	{0.002}	
	0.027	0.013	**0.012**	0.076
	(0.192)	(0.712)	(2.320)	
	[0.188]	[0.892]	[2.133]	
	{0.834}	{0.571}	{0.024}	

Table 2.4 One Period Ahead Forecast of ΔTBI_{t+1} related to EC_TAR_t

Table 2.6 reports the output from one period ahead regressions of the transaction based index return (ΔTBI_{t+1}) on EC_TAR (cointegrating residual for TBI and ABI and REITs), individually and combinatorically with $\Delta \mathrm{TBI}_t$ (the transaction based index return) and $\mathrm{DP}_{\mathrm{TBI}_t}$ (the dividend yield of the transaction based index). t-statistics are in parentheses, Newey-West t-statistics are in brackets, bootstrapped p-value are in braces and adjusted R square statistics are in the last column. Estimated coefficients that are significant for OLS, Newey-West and bootstrap estimations at the 5-percent level are highlighted in bold face. The sample spans the first quarter of 1994 to the fourth quarter of 2014.

$\Delta \mathrm{TBI}_{t+}$	$\Delta \mathrm{TBI}_t$	$\mathrm{DP\_TBI}_t$	$\mathrm{EC\_TAR}_t$	$\bar{R}^2$
			0.024	0.404
			(7.568)	
			[6.143]	
			{0.000}	
	0.134		**0.026**	0.401
	(1.423)		(7.218)	
	[1.406]		[5.377]	
	{0.502}		{0.000}	
		0.017	**0.024**	0.406
		(1.137)	(7.567)	
		[1.336]	[6.199]	
		{0.500}	{0.000}	
	0.120	0.012	**0.026**	0.392
	(1.251)	(0.793)	(7.102)	
	[1.255]	[0.945]	[5.316]	
	{0.52}	{0.554}	{0.000}	

Table 2.7 Comparison between Predictability of ΔTBI_{t+1} using EC_TA_t and EC_TAR_t

Table 2.7 reports the output from one period ahead regressions of the transaction based index return (ΔTBI_{t+1}) on EC_TA (cointegrating residual for TBI&ABI) and EC_TAR (cointegrating residual for TBI&ABI&REITs), respectively and altogether. t-statistics are in parentheses and adjusted R square statistics are in the last column. Estimated coefficients that are significant at the 5-percent level are highlighted in bold face. The sample spans the first quarter of 1994 to the fourth quarter of 2014.

ΔTBI_{t+1}	EC_TA_t	EC_TAR_t	$\bar{R}^2$
	0.012		0.103
	(3.291)		
	[2.954]		
	{0.002}		
		0.024	0.404
		(7.568)	
		[6.143]	
		{0.000}	
	-0.015	**0.036**	0.465
	(-3.216)	(7.530)	
	[-2.986]	[6.508]	
	{0.002}	{0.000}	

Table 2.8 OOS Forecast of ΔTBI_{t+1} Nested Comparison

The table 2.8 reports the output of one period ahead, nested forecast comparisons of transaction based index return $\Delta\mathrm{TBI}_{t+1}$. Rows 1,3,5,7 give forecast comparison of an unrestricted model including one period lagged dependent variable $\Delta\mathrm{TBI}_{t}$ and EC_TA_t or EC_TAR_t as the independent variable, with the autoregressive(AR) restricted model including only one period lagged dependent variable $\Delta\mathrm{TBI}_{t}$. Rows 2,4,6,7 give forecast comparison of an unrestricted model including a constant and EC_TA_t or EC_TAR_tas the independent variable, with the constant restricted model including only a constant. MSE_u is the mean squared error from the unrestricted model while MSE_r is the mean squared error from the restricted model. The ENC reports the modified Harvey, Leybourne and Newbold test statistic (Clark and McCracken 2001). MSE_F reports the output of out of sample F test. The 95th percentile of the asymptotic distribution of the statistic by Clark and McCracken 2001. The initial estimation period starts from 1stquarter of 1994 to the 4th quarter of 1999. The model is recursively reestimated until the 4th quarter of 2015.

Panel A: cointegration vector recursively re-estimated

			ENC		MSE_F	
	Comparison	MSE_u $/MSE_r$	Statistics	95%CV	Statistics	95%CV
1	EC_TA_t & AR	0.929	5.360	2.299	4.800	1.423
2	EC_TA_t & $Cons.$	0.953	5.866	2.266	3.024	1.437
3	EC_TAR_t & AR	0.605	34.465	2.261	39.072	1.439
4	EC_TAR_t & $Cons.$	0.583	35.446	2.596	41.968	1.806
Panel B: Fixed cointegration vector						
5	EC_TA_t & AR	0.906	7.162	2.665	6.646	1.794
6	EC_TA_t & $Cons.$	0.976	7.522	2.604	1.499	1.805
7	EC_TAR_t & AR	0.608	36.103	2.229	38.606	1.454
8	EC_TAR_t & $Cons.$	0.587	36.784	2.538	41.997	1.816

CHAPTER 3 : THE DETERMINANTS OF STOCK PRICE FLUCTUATION

3.1 Introduction

Investors' expectation of future cash flows and discount rates are essential in understanding stock price movements. Campbell and Shiller (1988) develop a log-linear dividend price ratio model and show that the dividend price ratio is determined by the present value of expected returns and the present value of expected dividend growth. In particular, using a variance decomposition they find that the discount rate news contributes about 50% to the variation of the dividend-price ratio. They also find that there is substantial variation of dividend price ratio that cannot be explained by fundamentals. However, more recent research has overturned this finding. For example, a variance decomposition of net payout yield from Larrain and Yogo (2008) shows that 88% is explained by expected cash flow growth while the remaining 12% of its variation is explained by expected asset returns (i.e., discount rate news). Additionally, using accounting earnings instead of dividends as a measure of cash flows, Sadka (2007) shows that as much as 70% of the variation in the dividend-price ratio can be explained by changes in expected earnings. Evans (1998) finds that future dividend growth change account for more than 90% of dividend yield variation. Lee (1998), using a structural VAR approach, documents that earnings or dividend can explain half of variation in price and time varying risk premium rather than time varying interest rate can help to explain much of remaining price variation. At the firm level, Vuolteenaho (2002) found firm-level stock returns are mainly driven by cash-flow news. For a typical stock, the variance of cash-flow news is more than twice that of expected-return news. As one can see, the stock price literature is contentious.

VAR and structural VAR methods have some limitations in correctly capturing the dynamics of investors' and econometricians' behavior. One standard approach in the literature is using a VAR model to extract these unobserved expectations. The generality of VAR models and the ability to

generate impulse-response functions and variance decompositions have made them a mainstay in the literature (e.g., Campbell, 1991; Campbell and Ammer, 1993). However, there are some inherent limitations to these models. VAR decompositions can be sensitive to the variables included in the VAR and the discount rate news results are contingent on the power of the model in capturing the time-variation of expected returns (Chen and Zhao, 2009).[10] To overcome some of the issues with VARs, the literature has turned to structural VARs. This method allows researchers to identify structural shocks given theoretical restrictions. Lee (1996, 1998) studies market price fluctuation by applying structural VAR, which allows him to decompose the stock price into four components. Although structural VARs seems more plausible in allowing us to extract structural shocks based on the identification of permanent effects and temporary effects on stock price, it is problematic to associate permanent effects to news and transitory effects to pure noise because if investors cannot differentiate the news from noise in a signal extraction context, neither do the econometricians (Blanchard, L'Huiller, and Lorenzoni, 2013).

Another branch of literature uses a state-space approach to estimate the expectation processes as latent factors (e.g., Balke and Wohar, 2002; Binsbergen and Koijen, 2010). The advantage of using the state space approach is that it not only can model expectations directly as latent factors, but is also able to capture potentially long-lasting serial correlations that a VAR model with finite number of lags cannot do. However, the simple state space model cannot capture the dynamics of investors and econometricians behavior correctly. In reality, investors receive information about the future and they cannot identify whether the shock is from fundamentals or noise. In the short run, investors make investment decisions based on their information and these decisions affect the stock price. In the long run, the stock price will jump to a new level if some information turns out to be fundamental while the stock price will come back to the original level if some information is

[10] Additionally, the validity of the model depends crucially on the asset price appearing as a state variable, however, empirical work has mostly neglected this issue. See Engsted, Pedersen and Tanggaard (2012) for more discussion relating to the misuse of VAR stock price decompositions in the empirical literature.

pure noise. Both dynamics of fundamental and noise shocks decide the short term and long term change of the stock price. The most commonly used state space models do not capture this process in its entirety. They rely solely on econometricians process and do not take into account the impact that the investors process has on price formation (Blanchard et al., 2013).

Our paper corrects for this deficiency in the traditional state space model. We apply the signal extraction model of Blanchard et al. (2013) to incorporate the investors signal acquisition and econometrician's signal extraction processes simultaneously. This allows us to derive three orthogonalized shocks: a fundamental permanent shock, a fundamental transitory shock, and a non-fundamental shock to explain stock price fluctuation. The signal extraction process can be broken up into three steps. Firstly, the investor receives a signal of the unobservable state variables from dividends and earnings, and updates his current expectations of these state variables, modeled using a Kalman filter. Secondly, the econometrician observes the change in price caused by the updated investor expectations and updates his expectations in turn. Lastly, we are able to solve for the econometrician's expectations using maximum likelihood methods.

Our paper also contributes to the vast discussion surrounding the fundamental cause of discount rate news. The literature has explained discount rate news as either being caused by time-varying risk premiums[11] or by behavioral factors.[12] Cochrane (1999) presents a consumption based model to measure the time varying risk premia using risk aversion, which capture much of the historical

[11] Fama and French (1989) found expected return contain time varying risk premium related to long-term business condition. Zhang (2005) analyzes the impact of this time-variation on capital investment and expected return within the neoclassical framework and argues countercyclical price of risk cause assets in place to be harder to reduce, and hence are riskier than growth options especially in bad times when the price of risk is high.

[12] For example, Lakonishok, Shleifer and Vishny (1994) provide evidence that value strategies yield high return because of it exploit the suboptimal behavior of typical investors not because these strategies are fundamental riskier. Lakonishok and Lee (2001) find evidence that insider trades are also able to predict the stock return.

stock market risk from consumption data.[13] Therefore, we use two common macro finance uncertainty measures, Cochrane's stochastic risk aversion and real GDP uncertainty, to further decompose the non-fundamental shock into time varying risk shock and pure noise.

The results show that the non-fundamental shock is more volatile than the fundamental permanent and fundamental transitory shocks. Both earnings and dividends are mainly driven by the fundamental permanent innovation. The non-fundamental shock contributes the majority portion to the variation of the dividend price ratio. Fundamental shock to log dividend price ratio are counteracted. This is due to the fact that the variation in each of the log dividends and log price are driven mainly by the fundamental shock. This fundamental component is then canceled out in the log dividend-price series. In full sample period from 1871 to 2015, the fundamental permanent and non-fundamental innovation contribute 44.9% and 54.5% individually to the price fluctuation.

We additionally find that time varying risk account for more than 30% of the non-fundamental component. Therefore, the importance of the time varying risk in explaining the stock price fluctuation is strengthened by the results. Our results hold in subsample robustness checks.

This paper casts a fresh eye on stock market behavior and contributes to the literature in several ways. The main contribution of this paper is to apply the signal extraction model of Blanchard et al. (2013) in studying the determinants of stock price fluctuation, which can simulate the investor's information acquisition process in making investment decision and econometrician signal extraction process in analyzing the stock market. In examining the shocks to the stock price fluctuation, we emphasize the theoretical rationale that econometrician extract information from the investor's information acquisition process. The signal extraction model reasonably captures this property in the investment process. The signal extraction model generates more accurate parameter estimation for stock variables, and provides a more precise decomposition of stock price

[13] In a similar work, Brandta and Wang (2003) formulate a consumption-based asset pricing model in which aggregate risk aversion is time-varying in response to both news about consumption growth (as in a habit formation model) and news about inflation.

fluctuations. Secondly, two prevalent time varying risk measures based on asset pricing theory are used to decompose the non-fundamental shock into a time varying risk shock and a mispricing shock. Our results provide evidence that the ability of the time varying risk in explaining the stock price fluctuation is nontrivial. These two separated shocks can help investors to better understand the interpretation of the discount rate news and the stock price fluctuation.

The remainder of this paper is organized as follows. Section 3.2 introduces the methodology used to identify the parameters through signal extraction and the data employed in this study. Section 3.3 report the empirical results. Section 3.4 further decompose the non-fundamental component. Section 3.5 concludes.

3.2 Model and Data

In this section, we introduce our model. Earnings are assumed to be driven by two fundamental shocks: a permanent shock and a transitory shock. Investors generally cannot distinguish these two shocks, and only observe reported net income. The permanent shock introduces uncertainty about the firm's long-run fundamentals. The presence of the transitory shock implies that investors cannot back out the permanent shock from earnings, thus creating a signal extraction problem. To capture the idea that they have more information than just current and past earnings, we allow the investor to observe an additional signal about the permanent component of earnings. This signal adds a third source of variation, which we call "non-fundamental shock." Agents make investment decisions based on their expectations and their signal extraction process. Their investment decisions determine stock price in the short run. Thus, the dynamics of dividend yield are determined by three types of shocks, the two shocks to earnings: the fundamental permanent shock and the fundamental transitory shock; and the non-fundamental shock.

3.2.1 Earnings

Let the log of real earnings during period t be NI_t. I decompose the earnings as the sum of a permanent earnings x_t and transitory earnings z_t. The non-stationary permanent component x_t follows a unit root process and the stationary component z_t follows a AR (1) process,

$$NI_t = x_t + z_t \tag{3.1}$$

$$\Delta x_t = \rho_x \Delta x_{t-1} + \varepsilon_t \tag{3.2}$$

$$z_t = \rho_z z_{t-1} + \eta_t \tag{3.3}$$

where ε_t and η_t are permanent and temporary innovations, respectively. ε_t and η_t are i.i.d. normal with variance σ_ε^2 and σ_η^2, respectively.

Observing current earnings information, investors receive a noisy signal of permanent earnings, s_t , which incorporates permanent earnings and noise,

$$s_t = x_t + v_t \tag{3.4}$$

$$v_t = \rho_v v_{t-1} + \xi_t \tag{3.5}$$

where v_t is AR (1) with a noise shock ξ_t, which is i.i.d. normal with variance σ_ξ^2. It is worth noting that s_t is directly observable to investors but not to econometricians. For econometricians, the signal s_t is unobservable but earnings NI_t and the dividend price ratio DP_t are observable.

3.2.2 Dividend Price Ratio

Campbell and Shiller (1998) propose a log-linear dividend price ratio model, arguing that the log dividend price ratio provides the optimal forecast of the present value of expected future returns or the present value of expected future dividend growth, or both:

$$d_t - p_t = \frac{-K}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j \left[-\Delta d_{t+1+j} + r_{t+1+j} \right] \tag{3.6}$$

Where d_t is the log dividend, p_t is the log price, ρ is the discount factor less than one, Δ is one period backward difference and r is the log stock return.

The literature suggests that dividends reflect long-run permanent earnings (Lintner, 1956; Brav, Graham, Harvey, and Michaely, 2005). Without loss of generality, we allow that firms make dividend policy based on their long term and short term earnings, i.e., permanent component of earnings x_t and temporary component of earnings z_t. We assume dividend growth follows a AR (1) process. We additionally assume that dividends are proportional to earnings

$$D_t = \alpha_1 x_t + \alpha_2 z_t \tag{3.7}$$

Note that for any stationary series h_t following an AR (1) process, we have

$$E_t \sum_{j=0}^{\infty} \rho^j \left[h_{t+1+j}\right] = E_t \sum_{j=0}^{\infty} \rho^j {\rho_h}^{j+1} [h_t] = \frac{\rho_h}{1-\rho\rho_h} h_{t|t} \tag{3.8}$$

Based on the assumption D_t follows AR (1) process, we can get expected value of dividend growth in the long run,

$$E_t \sum_{j=0}^{\infty} \rho^j \left[\Delta d_{t+1+j}\right] = \frac{\alpha_1 \rho_x}{1-\rho\rho_x}\left(x_{t|t} - x_{t-1|t}\right) + \frac{\alpha_2 \rho_z}{1-\rho\rho_z}\left(z_{t|t} - z_{t-1|t}\right) \tag{3.9}$$

Where $x_{t|t}$ and $x_{t-1|t}$ represent the conditional expectation of unobservable states x_t and x_{t-1} given all the information available at time *t*.

Campbell and Shiller (1988) found that discount rate news is correlated with cash flow news. This implies that the discount rate contains both firms' fundamental information and non-fundamental information. Consequently, we assume that the discount rate is associated with the permanent, transitory component of earnings and another factor v_t which is associated with time varying risk premium or mispricing or both. As a result, we have $r_t = \beta_1 \Delta x_t + \beta_2 z_t + \beta_3 v_t$. According to equation (3.7), the discount rate part can be similarly derived as:

$$E_t \sum_{j=0}^{\infty} \rho^j \left[r_{t+1+j}\right] = E_t \sum_{j=0}^{\infty} \rho^j \left(\beta_1 \Delta x_t + \beta_2 z_t + \beta_3 v_t\right)$$

$$= \frac{\beta_1 \rho_x}{1 - \rho\rho_x}\left(x_{t|t} - x_{t-1|t}\right) + \frac{\beta_2 \rho_z}{1 - \rho\rho_z} z_{t|t} \qquad (3.10)$$

$$+ \frac{\beta_3 \rho_v}{1 - \rho\rho_v} v_{t|t}$$

Finally, to get Campbell Shiller dividend price ratio, we add equations (3.9) and (3.10):

$$d_t - p_t = \frac{(\beta_1 - \alpha_1)\rho_x}{1 - \rho\rho_x} x_{t|t} + \frac{(\alpha_1 - \beta_1)\rho_x}{1 - \rho\rho_x} x_{t-1|t} + \frac{(\beta_2 - \alpha_2)\rho_z}{1 - \rho\rho_z} z_{t|t}$$

$$+ \frac{\alpha_2 \rho_z}{1 - \rho\rho_z} z_{t-1|t} + \frac{\beta_3 \rho_v}{1 - \rho\rho_v} v_{t|t} \qquad (3.11)$$

The dividend price ratio can be expressed by the expectation of the permanent and transitory components of earnings and a non-fundamental component. Campbell Shiller's dividend price ratio is composed of cash flow news and discount rate news, which are correlated. Our model has the advantage in that we decomposed the dividend-price ratio into three orthogonalized shocks: fundamental permanent, fundamental transitory and non-fundamental, so that their impacts on the dividend price ratio are easier to identify.

To make comparison with the existing literature, we adopted Campbell 1991 to extract stock price behavior as follows:

$$p_t = \alpha_1 x_t + \alpha_2 z_t - \left(\frac{(\beta_1 - \alpha_1)\rho_x}{1 - \rho\rho_x}\right) x_{t|t} - \left(\frac{(\alpha_1 - \beta_1)\rho_x}{1 - \rho\rho_x}\right) x_{t-1|t}$$

$$- \left(\frac{(\beta_2 - \alpha_2)\rho_z}{1 - \rho\rho_z}\right) z_{t|t} - \frac{\beta_2 \rho_z}{1 - \rho\rho_z} z_{t-1|t} \qquad (3.12)$$

$$- \frac{\beta_3 \rho_v}{1 - \rho\rho_v} v_{t|t}$$

The variance decomposition of the stock price is based on equation (3.12)

3.2.3 Model Identification

Next, we need to solve the investors signal extraction problem through expressing two observable variables NI_t and DP_t by three shocks ε_t, η_t, ξ_t. It is easy to bring this process down to two steps. First, we establish the linkage between observable variables NI_t and DP_t with current and lagged expectations of these unobservable states x_t, z_t, and v_t in equation (3.1), (3.7) and (3.11). The second step is to derive the dynamics of those expectation of unobservable states. The two steps work together to help us to link two observable variables and three shocks in a signal extraction system.

Let us start from the investors side first. Investors can observe current earnings NI_t and receive a signal s_t, which help them to make investment decisions. So the observation function for the investors is given as:

$$\begin{bmatrix} NI_t \\ D_t \\ s_t \end{bmatrix} = D \begin{bmatrix} x_t \\ x_{t-1} \\ z_t \\ z_{t-1} \\ v_t \end{bmatrix} \tag{3.13}$$

$$\text{where } D := \begin{bmatrix} 1 & 0 & 1 & 0 & 0 \\ \alpha_1 & 0 & \alpha_2 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

The investor's state vector is $\mathrm{I}_t = \{x_t, x_{t-1}, z_t, z_{t-1}, v_t\}'$, and the dynamics of state vector can be derived using Kalman filter. So the state equation for the investors is given as:

$$\begin{bmatrix} x_t \\ x_{t-1} \\ z_t \\ z_{t-1} \\ v_t \end{bmatrix} = \begin{bmatrix} 1+\rho_x & -\rho_x & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_z & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \rho_v \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ z_{t-2} \\ v_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \\ \eta_t \\ 0 \\ \xi_t \end{bmatrix} \tag{3.14}$$

$$\text{We define } C := \begin{bmatrix} 1+\rho_x & -\rho_x & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_z & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \rho_v \end{bmatrix},$$

with covariance matrix $\Sigma_1 = \begin{bmatrix} \sigma_\varepsilon^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_\eta^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_\xi^2 \end{bmatrix}$

Let P=$\sigma_{t-1}^2[\mathrm{I}_t]$, P matrix can be solved by equation $P = C[P - PD'(DPD')^{-1}DP]C' + \Sigma_1$.

Then we define A and B matrix as $A = (I - BD)C$ and $B = PD'(DPD')^{-1}$. Combing observation equation (3.13) and state equation (3.14), we get

$$\begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \\ z_{t-1|t} \\ v_{t|t} \end{bmatrix} = A \begin{bmatrix} x_{t-1|t-1} \\ x_{t-2|t-1} \\ z_{t-1|t-1} \\ z_{t-2|t-1} \\ v_{t-1|t-1} \end{bmatrix} + B \begin{bmatrix} NI_t \\ D_t \\ s_t \end{bmatrix} \tag{3.15}$$

Through observing Earnings NI_t and receiving a signal s_t, the investor updates his expectations through the Kalman filter. Expand equation NI_t and s_t in (3.15) using equations (3.1) -(3.5) to get the investor's signal extraction problem.

$$\begin{aligned} \begin{bmatrix} x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \\ z_{t-1|t} \\ v_{t|t} \end{bmatrix} &= A \begin{bmatrix} x_{t-1|t-1} \\ x_{t-2|t-1} \\ z_{t-1|t-1} \\ z_{t-2|t-1} \\ v_{t-1|t-1} \end{bmatrix} + B \begin{bmatrix} 1+\rho_x & -\rho_x & \rho_z & 0 & 0 \\ (1+\rho_x)\alpha_1 & -\rho_x\alpha_1 & \rho_z\alpha_2 & 0 & 0 \\ 1+\rho_x & -\rho_x & 0 & 0 & \rho_v \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ z_{t-2} \\ v_{t-1} \end{bmatrix} \\ &+ B \begin{bmatrix} 1 \\ \alpha_1 \\ 1 \end{bmatrix} \varepsilon_t + B \begin{bmatrix} 1 \\ \alpha_2 \\ 0 \end{bmatrix} \eta_t + B \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \xi_t \end{aligned} \tag{3.16}$$

Having derived the investor's signal extraction problem, we next turn to the econometrician's view. Recall that on the econometrician's side, only earnings NI_t and dividend ratio DP_t are observable. So the econometrician's observation equation is given as

$$\begin{bmatrix} NI_t \\ D_t \\ DP_t \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_1 & 0 & \alpha_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{(\beta_1-\alpha_1)\rho_x}{1-\rho\rho_x} & \frac{(\alpha_1-\beta_1)\rho_x}{1-\rho\rho_x} & \frac{(\beta_2-\alpha_2)\rho_z}{1-\rho\rho_z} & \frac{\alpha_2\rho_z}{1-\rho\rho_z} & \frac{\beta_3\rho_v}{1-\rho\rho_v} \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ z_t \\ z_{t-1} \\ v_t \\ x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \\ z_{t-1|t} \\ v_{t|t} \end{bmatrix} \quad (3.17)$$

The econometrician's state vector is $\mathrm{I}_t = \{x_t, x_{t-1}, z_t, v_t, x_{t|t}, x_{t-1|t}, z_{t|t}, v_{t|t}\}'$ and we express the state equation as

$$\begin{bmatrix} x_t \\ x_{t-1} \\ z_t \\ z_{t-1} \\ v_t \\ x_{t|t} \\ x_{t-1|t} \\ z_{t|t} \\ z_{t-1|t} \\ v_{t|t} \end{bmatrix} = \begin{bmatrix} \begin{matrix} 1+\rho_x & -\rho_x & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_z & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \rho_v \end{matrix} & \begin{matrix} 0_{1*5} \\ 0_{1*5} \\ 0_{1*5} \\ 0_{1*5} \\ 0_{1*5} \end{matrix} \\ B \begin{bmatrix} 1+\rho_x & -\rho_x & \rho_z & 0 & 0 \\ (1+\rho_x)\alpha_1 & -\rho_x\alpha_1 & \rho_z\alpha_2 & 0 & 0 \\ 1+\rho_x & -\rho_x & 0 & 0 & \rho_v \end{bmatrix} & A_{5*5} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ z_{t-1} \\ z_{t-2} \\ v_{t-1} \\ x_{t-1|t} \\ x_{t-2|t} \\ z_{t-1|t} \\ z_{t-2|t} \\ v_{t-1|t} \end{bmatrix}$$

$$+ \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ B \begin{bmatrix} 1 & 0 & 0 \\ \alpha_1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} & +B \begin{bmatrix} 0 & 1 & 0 \\ 0 & \alpha_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} & +B \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \eta_t \\ \xi_t \end{bmatrix} \quad (3.18)$$

Through equation (3.17) and (3.18), we can solve the econometrician's filtering problem. Note that the investors updating process (3.16) has already been included in the econometrician's expectation updates (3.18) and econometricians can figure out the investors state vector by

observing the dividend ratio DP_t. Therefore, we can use econometrician's kalman filter to establish the maximum likelihood function.

This paper adopts maximum likelihood approach to estimate the parameters ρ_x , ρ_z , $\rho_v, \alpha_1, \alpha_2, \beta_1, \beta_2, \beta_3$, σ_ε^2 σ_η^2 and σ_ξ^2 in sense that it can incorporate all the restrictions in the model.

3.2.4 Data

For the whole sample, I obtain annual observations on real stock price, real earnings, and real dividends from Robert Shiller Index for period 1871-2015. All three series, earnings (NI_t), stock price (p_t) and dividends (d_t) are in log form. And dividend price ratio is computed by difference of d_t and p_t. For subsample estimation, I use quarterly and annually observations from Robert Shiller Index for period 1968-2015.

3.3 Empirical Results

3.3.1 Model Estimation

In our empirical study, we solve the investors signal extraction problem and then construct the econometrician's Kalman filter through the unobservable states. We establish the likelihood function using the econometrician's Kalman filter to estimate the parameters. The maximum likelihood estimation results are presented in table 3.1. Note the parameter ρ, the discount rate, is set as 0.95 for convenience. Table 3.1 reports the estimated parameters under the signal extraction model using annual data from 1871 to 2015. The coefficients ρ_x and ρ_z are not persistent, which match the property of the stationary series. The only persistent parameter is ρ_v = 0.93, implying slowly decaying non-fundamental shocks. This paper will further decompose the non-fundamental shock in section 3.4. The persistence of the non-fundamental shock comes from the time varying risk. The standard deviations of the three shocks are σ_ε^2 = 0.127, σ_η^2 = 0.213 and σ_ξ^2 = 0.703, respectively. The non-fundamental shock is more volatile than fundamental shock because it

incorporates the noise shock. The fundamental transitory shock is more volatile than the fundamental permanent shock. The dividend weight α_1 is 0.8872 while α_2 is -0.125, implying that the dividend policy is mainly and positively determined by permanent earnings and transitory earnings only play a small role in the dividend decision. The return weights β_1 and β_2 are significant but β_3 is not. This occurs because the expected return is affected by fundamental permanent and fundamental transitory components but not the non-fundamental component.

3.3.2 Impulse Response and Variance Decomposition

From the signal extraction model in section 3.3, the dynamic impulse response and forecast error variance decomposition can be achieved using the estimated parameters. Figure 3.1 illustrates that the dynamic responses of earnings (NI_t), dividend yield (DP_t), dividend (D_t) and stock price (P_t) to fundamental permanent, fundamental transitory and non-fundamental shocks.

Figure 3.1 illustrates that the fundamental permanent innovation has a strong, persistent effect on earnings, whereas fundamental transitory innovation has a strong initial effect and then its effects decay in a few years. This indicates that temporary changes in earnings constitute a nontrivial part of earnings initially but only permanent innovation determines the income in the long run. Changes in dividends is primarily influenced by changes in permanent innovations consistently and transitory innovation only plays a small role and decays in two periods. For the dividend price ratio, the fundamental permanent innovation has a positive influence on both dividend and price. Therefore, the log difference of the dividend price ratio is merely influenced by fundamental innovations. For the same reason, the fundamental transitory innovation has almost no impact on the dividend yield. However, the non-fundamental innovation has a significantly positive impact on dividend yield and this impact decays after a few years. Most importantly, stock price has strong and persistent response to the fundamental permanent innovation and a weak,

initial under-reaction to the fundamental transitory innovation. Non-fundamental innovation has a significant negative impact on the price but this impact decrease with time.

Table 3.2 presents the variance decomposition of fundamental permanent, fundamental transitory and non-fundamental shocks from 1 to 24 quarters ahead. The main result is that in short run, fundamental permanent shock account for 26.1% of earning volatility at a 1-quarter horizon and more than 50% at a 4-year horizon, while fundamental transitory shock plays a bigger role in the beginning but a smaller role after 4 years, explaining less than 50% at a 4-year horizon. Most of dividend yield is explained by the non-fundamental shock and this implies that both dividends and price are primarily affected by the fundamental changes so that the ratio is mainly affected by the non-fundamental changes. Dividends are mainly determined by permanent earnings, which is consistent with the hypothesis that dividend change is primarily influenced by changes in permanent earning. Initially, about half the variation in prices is accounted for by non-fundamental innovations but their importance declines as the time horizon increases. The other half comes from fundamental permanent innovations but their importance increases as the time horizon increases. The fundamental transitory innovation has almost no effect on the variation of the price. After 24 years, the fundamental permanent component accounts for 85.4% of price volatility while non-fundamental shock only account for 14.3%. This finding casts doubt on the notion that changes in stock prices arise solely from changes in market fundamentals such as earnings and dividends. The results suggest the importance of further decomposition of the non-fundamental innovation. From here, the question naturally arises whether the non-fundamental innovation is pure noise or both time varying risk and noise. The next section will introduce the further decomposition of non-fundamental shock into time varying risk component and noise component.

3.3.3 Sub-period Analysis

The long-time period is subject to contamination from periods of regime switching and war. We adopt the sub-period analysis from 1968 to 2015 quarterly and annually for the following two reasons. Firstly, this post-war period is relatively tranquil. Secondly, this time period matches the further decomposition of non-fundamental component exercise, in which the data availability of one risk measure, the dispersion of GDP forecast, starts from 1968. Table 3.3 and Table 3.4 are the parameter estimation and variance decomposition using the data from the fourth quarter of 1968 to the fourth quarter of 2015 under the signal extraction model while Table 3.5 and Table 3.6 are the parameter estimation and variance decomposition using annual frequency data from 1968 to 2015.

Table 3.3 and Table 3.5 reports the parameters estimation under the maximum likelihood method for quarterly and annual data from 1968 to 2015, respectively. The main results in subsample are similar to the results in whole sample. The coefficients ρ_x is not persistent both quarterly and annually. However, ρ_z is not persistent in annual frequency but persistent in quarterly frequency, which indicates that the transitory shock in quarterly frequency decays slower than in annual frequency. The persistence of parameter ρ_v is the same as whole sample estimation. The standard deviation of non-fundamental shock is highest in three shocks and the fundamental transitory shock is more volatile than fundamental permanent shock. The dividend weight α_1 is significantly positive while α_2 is small or insignificant. Therefore, permanent earnings are still the main concern of the dividend policy. The magnitude of return weight β_1 is higher than β_2 and β_3, which implies that expected return is affected by fundamental permanent than the fundamental transitory components and the non-fundamental component. In the subsample period β_3 is significant, indicating that the non-fundamental component has an effect on the expected return due to the reason that econometrician has better knowledge of time varying risk in recent period.

Figure 3.2 and figure 3.3 plot the impulse response function of earnings (NI_t), dividend yield (DP_t), dividend (D_t) and stock price (P_t) to fundamental permanent, fundamental transitory and

non-fundamental shocks for quarterly and annual subsample from 1968 to 2015, respectively. The big picture is the same between sample from 1968 and the whole sample: The earning is mainly determined by fundamental permanent innovation in long run the fundamental transitory innovation has a strong initial effect. Dividend policy is also mainly determined by the permanent innovations instead of transitory innovations. For the dividend price ratio, the fundamental permanent innovation has a positive influence on both dividend and price. Therefore, the log spread of dividend price ratio is merely influenced by fundamental innovation. Additionally, the non-fundamental innovation has a significantly positive impact on dividend yield and this impact decays after a few years. Both the fundamental permanent innovation and non-fundamental innovation contribute to the stock price variation. There is no big difference between quarterly results and annual results. The impulse response of the quarterly frequency data is smoother than the annual frequency data due to the shortening of data frequency.

Table 3.4 and 3.6 present the variance decomposition of fundamental permanent, fundamental transitory and non-fundamental shocks from 1 to 24 quarters ahead for annual subsample and quarterly subsample. Most of dividend yield is explained by the non-fundamental shock. Note in the subsample, is the non-fundamental shock contributes even more to the dividend price ratio than the whole sample. It means the non-fundamental plays a more important role in explaining the stock price fluctuation. Initially, about 73% the variation in prices is accounted for by non-fundamental innovations but their importance declines as the time horizon increases. Another 25.7% comes from the fundamental permanent innovations but their importance increases as the time horizon increases. The fundamental transitory innovation has almost no effect on the variation of the price. After 24 years, the fundamental permanent account for 58.7% of price volatility while non-fundamental shock only account for 41.3%. The results also suggest the importance of further decomposing the non-fundamental innovation. Additionally, there is no big difference between quarterly results and annual results. The variance decomposition of the

quarterly frequency data is more persistent than the annual frequency data due to the shortening of data frequency.

3.4 Decomposition of Non-Fundamental Component

3.4.1 Real GDP Uncertainty

The measure of real economy uncertainty we adopt is the dispersion in respondents' expectation for real GDP growth over the next four quarters. The dispersion measure we use is the difference between the 90th percentile and the 10th percentile of all responses, and is denoted by dpGDP.

3.4.2 Habit-Based Risk Aversion

We use the measure of risk aversion based on the habit-based model by Campbell and Cochrane (1999). CC use a model of external habit to motivate stochastic risk aversion, the log of which we denote as ra. The construction of risk aversion series follows Bekaert and Engstrom (2010), who summarized Campbell and Cochrane 's external habit model. The values for real nondurables and services consumption log growth are from the NIPA tables.

3.4.3 The Decomposition of Non-Fundamental Component

The fitted value $c_0 + c_1 * ra_t + c_2 * dpGDP_t$ is the time-varying risk component (TVR_t) while u_t is the noise component. Take variance of both time-varying risk component (TVR_t) and noise component (u_t), we can calculate the proportion of Var (TVR_t)/ [Var (u_t)+ of Var (TVR_t)] and Var (u_t)/ [Var (u_t)+ of Var (TVR_t)]. The results are reported in Table 3.7. The time varying risk component and noise component contribute 34.2% and 65.8% individually for the quarterly frequency data, and 26.2% and 73.8% for the annual frequency data. Therefore, the time varying risk is an in-negligible part in the non-fundamental component of stock return.

$$v_t = c_0 + c_1 * ra_t + c_2 * dpGDP_t + u_t \tag{3.19}$$

3.5 Conclusion

The decomposition of stock price is of paramount importance to investors and researchers since both the fundamental shock and non-fundamental shock drive the direction of the sign and magnitude of stock price movements. In this paper, we reexamine the determinants of stock price fluctuation with application of signal extraction model. The advantage of this model is that it can simulate the investors' investment decision formation process. Using a maximum likelihood estimation, we show that the fundamental permanent shock and non-fundamental shock contribute almost 50% to stock price fluctuation, respectively. The fundamental transitory shock does not play an important role in determining the stock price. Our robustness checks imply the stability and viability of the signal extraction model in asset pricing.

Additionally, by adopting two plausible measures of time varying risk, the non-fundamental component is further decomposed into time varying risk and noise components. The time varying component account for more than 30% in the non-fundamental component. Therefore, we argue that the time varying risk is an essential component in explaining the stock price fluctuation.

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Tables

Table 3.1 Maximum Likelihood Estimation 1871A:2015A

Table 3.1 reports the estimated parameters from signal extraction model with t-statistics displayed in parentheses. The data spans from 1871 to 2015 annually.

Parameters	Definition	Estimates
ρ_x	Fundamental permanent component persistence	0.141**
		(1.900)
ρ_z	Fundamental temporary component persistence	0.456***
		(6.449)
ρ_v	Non-Fundamental component persistence	0.929***
		(29.467)
α_1	Sensitivity of dividend to fundamental permanent component	0.887***
		(7.568)
α_2	Sensitivity of dividend to fundamental temporary component	-0.125***
		(3.013)
β_1	Sensitivity of risk to fundamental permanent component change	1.820***
		(2.305)
β_2	Sensitivity of risk to fundamental temporary component	-0.345***
		(3.002)
β_3	Sensitivity of risk to non-fundamental component	0.026
		(1.117)
σ_ε^2	Fundamental permanent shock variance	0.127***
		(7.659)
σ_η^2	Fundamental temporary shock variance	0.213***
		(13.921)
σ_ξ^2	Non-Fundamental shock variance	0.703
		(1.222)

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Table 3.2 Relative Importance of Permanent Shock (ε_t), Temporary Shock (η_t) and Non-Fundamental Shock (ξ_t) in Forecasting Four Variables 1871A:2015A

Table 3.2 reports the relative importance of fundamental permanent shock (ε_t), fundamental temporary shock (η_t) and non-fundamental shock (ξ_t) in explaining four important variables: earnings (NI_t), dividend yield (DP_t), dividend (D_t) and stock price (P_t) for various forecasting horizons (1 to 24 years). For example, at one year horizon, 44.9% of the forecast error variance of P_t is explained by ε_t, 0.6% by η_t, and 54.5% by ξ_t. The data spans from 1871 to 2015 annually.

	Variables Explained											
	NI_t			DP_t			D_t			P_t		
Forecast	Innovations in											
Horizons	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t
1	0.261	0.739	0	0.030	0.116	0.854	0.947	0.053	0	0.449	0.006	0.545
2	0.402	0.598	0	0.017	0.128	0.855	0.971	0.029	0	0.545	0.019	0.435
4	0.584	0.416	0	0.010	0.089	0.901	0.986	0.014	0	0.630	0.011	0.360
8	0.745	0.255	0	0.007	0.061	0.932	0.993	0.007	0	0.711	0.006	0.283
12	0.816	0.184	0	0.006	0.053	0.941	0.996	0.005	0	0.764	0.004	0.232
24	0.900	0.100	0	0.005	0.047	0.950	0.998	0.002	0	0.854	0.002	0.143

Table 3.3 Maximum Likelihood Estimation 1968Q4:2015Q4

Table 3.3 reports the estimated parameters from signal extraction model with t-statistics displayed in parentheses. The data spans from 1968 to 2015 quarterly.

Parameters	Definition	Estimates
ρ_x	Fundamental permanent component persistence	0.620***
		(10.758)
ρ_z	Fundamental temporary component persistence	0.902***
		(21.382)
ρ_v	Non-Fundamental component persistence	0.985***
		(74.724)
α_1	Sensitivity of dividend to fundamental permanent component	5.152***
		(5.113)
α_2	Sensitivity of dividend to fundamental temporary component	-0.001
		(0.095)
β_1	Sensitivity of risk to fundamental permanent component change	5.152***
		(5.118)
β_2	Sensitivity of risk to fundamental temporary component	-0.026**
		(2.125)
β_3	Sensitivity of risk to non-fundamental component	0.006**
		(1.983)
σ_ε^2	Fundamental permanent shock variance	0.003***
		(5.195)
σ_η^2	Fundamental temporary shock variance	0.155***
		(19.382)
σ_ξ^2	Non-Fundamental shock variance	0.875**
		(1.988)

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively.*

Table 3.4 Relative Importance of Permanent Shock (ε_t), Temporary Shock (η_t) and Non-Fundamental Shock (ξ_t) in Forecasting Four Variables 1968Q4:2015Q4

Table 3.4 reports the relative importance of fundamental permanent shock (ε_t), fundamental temporary shock (η_t) and non-fundamental shock (ξ_t) in explaining four important variables: earnings (NI_t), dividend yield (DP_t), dividend (D_t) and stock price (P_t) for various forecasting horizons (1 to 24 years). For example, at one year horizon, 3.4% of the forecast error variance of P_t is explained by ε_t, 9% by η_t, and 87.6% by ξ_t. The data spans from 1968Q4 to 2015Q4 quarterly.

	Variables Explained											
	NI_t			DP_t			D_t			P_t		
Forecast	Innovations in											
Horizons	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t
1	0.000	1.000	0	0	0.094	0.906	1	0	0	0.034	0.090	0.876
2	0.001	0.999	0	0	0.089	0.911	1	0	0	0.061	0.083	0.856
4	0.002	0.999	0	0	0.078	0.922	1	0	0	0.106	0.069	0.825
8	0.003	0.997	0	0	0.061	0.939	1	0	0	0.159	0.051	0.790
12	0.005	0.995	0	0	0.049	0.951	1	0	0	0.190	0.040	0.771
24	0.010	0.990	0	0	0.032	0.968	1	0	0	0.240	0.024	0.733

Table 3.5 Maximum Likelihood Estimation 1968A:2015A

Table 3.5 reports the estimated parameters from signal extraction model with t-statistics displayed in parentheses. The data spans from 1968 to 2015 annually.

Parameters	Definition	Estimates
ρ_x	Fundamental permanent component persistence	0.541**
		(4.169)
ρ_z	Fundamental temporary component persistence	0.263***
		(1.663)
ρ_v	Non-Fundamental component persistence	0.940***
		(18.558)
α_1	Sensitivity of dividend to fundamental permanent component	0.622***
		(2.776)
α_2	Sensitivity of dividend to fundamental temporary component	-0.0891***
		(4.357)
β_1	Sensitivity of risk to fundamental permanent component change	0.615***
		(2.677)
β_2	Sensitivity of risk to fundamental temporary component	-0.138***
		(0.714)
β_3	Sensitivity of risk to non-fundamental component	0.002
		(1.352)
σ_ε^2	Fundamental permanent shock variance	0.075***
		(3.005)
σ_η^2	Fundamental temporary shock variance	0.272***
		(9.111)
σ_ξ^2	Non-Fundamental shock variance	7.322
		(1.182)

*Statistical significance is denoted by ***, ** and * for 1%, 5% and 10% respectively*

Table 3.6 Relative Importance of Permanent Shock (ε_t), Temporary Shock (η_t) and Non-Fundamental Shock (ξ_t) in Forecasting Four Variables 1968A:2015A

Table 3.6 reports the relative importance of fundamental permanent shock (ε_t), fundamental temporary shock (η_t) and non-fundamental shock (ξ_t) in explaining four important variables: earnings (NI_t), dividend yield (DP_t), dividend (D_t) and stock price (P_t) for various forecasting horizons (1 to 24 years). For example, at one year horizon, 25.7% of the forecast error variance of P_t is explained by ε_t, 1.3% by η_t, and 73.0% by ξ_t. The data spans from 1968 to 2015 annually.

	Variables Explained											
	NI_t			DP_t			D_t			P_t		
Forecast	Innovations in											
Horizons	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t	ε_t	η_t	ξ_t
1	0.071	0.929	0	0.067	0.001	0.932	0.789	0.211	0	0.257	0.013	0.730
2	0.194	0.806	0	0.047	0.003	0.950	0.922	0.078	0	0.287	0.007	0.706
4	0.432	0.568	0	0.029	0.002	0.969	0.974	0.026	0	0.334	0.004	0.662
8	0.672	0.328	0	0.019	0.001	0.980	0.990	0.010	0	0.403	0.002	0.595
12	0.772	0.228	0	0.015	0.001	0.984	0.994	0.006	0	0.459	0.002	0.540
24	0.882	0.119	0	0.012	0.001	0.987	0.997	0.003	0	0.587	0.001	0.413

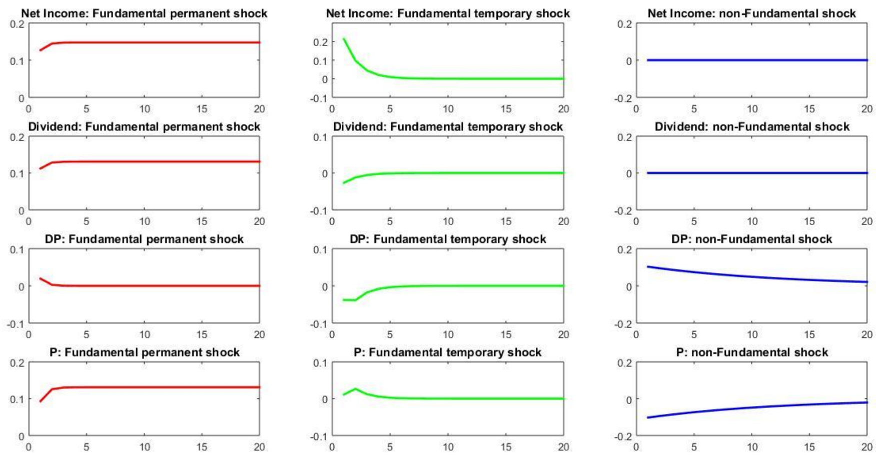
Table 3.7 Variance Decomposition of Non-Fundamental Component

Table 3.7 reports the relative importance of time varying risk (TVR_t) and noise (u_t) in non-fundamental component (v_t).

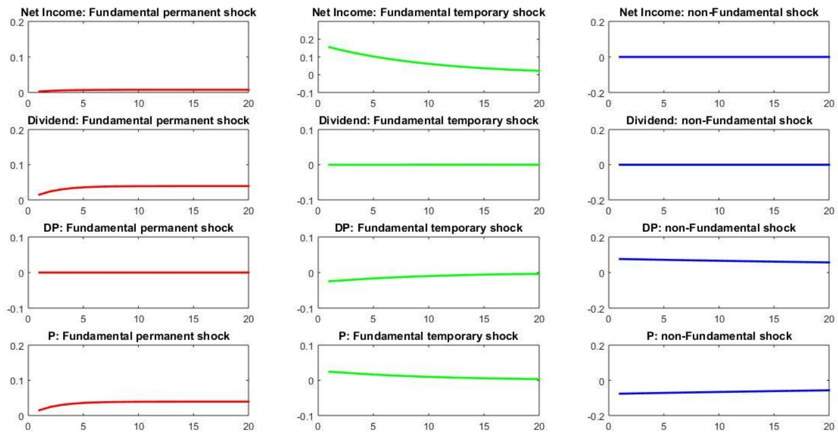
	Time Varying Risk (TVR_t)	Noise (u_t)
Panel A: 1968Q4:2015Q4	0.342	0.658
Panel B: 1968A:2015A	0.262	0.738

Figures

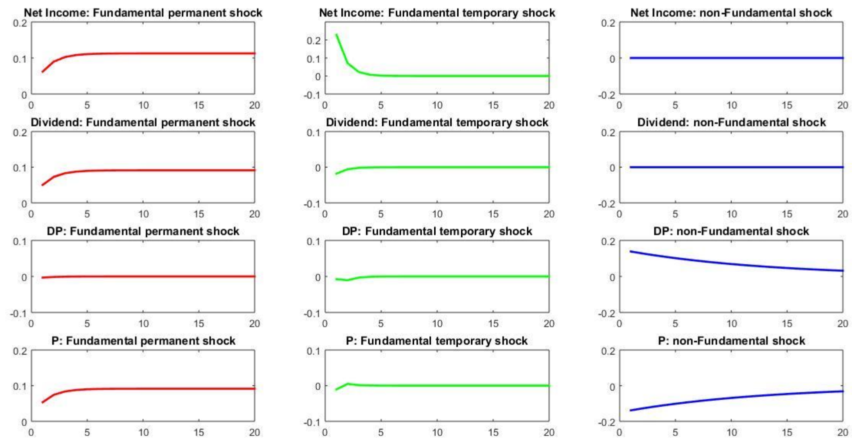
3.1 Responses of Log Earnings, Dividend, Dividend Yield and Price to Fundamental Permanent, Fundamental Transitory, and Non-Fundamental Innovations for 1871A:2015A



3.2 Responses of Log Earnings, Dividend, Dividend Yield and Price to Fundamental Permanent, Fundamental Transitory, and Non-Fundamental Innovations for 1968Q:2015Q



3.3 Responses of Log Earnings, Dividend, Dividend Yield and Price to Fundamental Permanent, Fundamental Transitory, and Non-Fundamental Innovations for 1968A:2015A



VITA

QIANYING ZHANG

2005-2009	B.S., Economics East China Normal University Shanghai, China
2009-2010	M.S., Economics University of Illinois, Urbana-Champaign Champaign, Illinois
2011-2013	M.S., Economics Florida International University Miami, Florida
2011 -2017	Doctoral Candidate in Economics Florida International University Miami, Florida

PUBLICATIONS AND PRESENTATIONS

Zhang, Q., Dupoyet, B., and Jiang, X. (2016). *A new take on the relationship between interest rates and credit spreads.* Under Review.

Zhang, Q., Dupoyet, B., and Jiang, X. (March 2016). *A new take on the relationship between interest rates and credit spreads.* Paper presented at the meeting of the Midwest Finance Association, Atlanta, Georgia.

Zhang, Q., Dupoyet, B., and Jiang, X. (November 2016). *A new take on the relationship between interest rates and credit spreads.* Paper presented at the meeting of the Southern Finance Association, San Destin, Florida.