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Systematic Mispricing: Evidence from Real Estate Markets

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by

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Dissertation Abstract

This dissertation consists three essays on empirical asset pricing. In Essay I, I conduct a comprehensive analysis of REITs pricing and I find that there is systematic mispricing in REIT markets. In Essay II, I study mispricing by using net asset value of REITs. I find that REIT prices deviate from their net asset value substantially. In Essay III, I study momentum crash and develop a new momentum trading strategy which has higher return and sharp ratio.

Essay 1: In this paper we apply recent developments in financial economics, which posit an important role for the leverage of financial intermediaries and limited stock market participation, in understanding real estate returns. We find that luxury consumption, funding liquidity and the capital share of income have significant explanatory power for the cross-section and time series of equity REITs. However, this relationship is the opposite of what we expected, and the results point to a more complex set of findings that are difficult to reconcile with risk-based explanations. Our results suggest systematic mispricing of real estate assets that is heavily influenced by investor sentiment.

Essay 2: Institutional investors are assumed to be sophisticated and rational, they are more likely to be the arbitrageurs who trade against mispricing. However, recent research suggests that institutional investors have a tendency to buy overvalued stock. Focusing on the REIT market, we find REIT stocks deviate substantially from their net asset value (NAV). The long-short strategy based on premium to NAV yields about 1% return monthly. We also find that, instead of correcting mispricing, institutional investors drive REIT prices away from their net asset value. Furthermore, our results may shed light on popular asset pricing anomalies. By checking the premium to NAV

of each anomaly portfolio, we conclude that ranking of momentum and earning surprise could be used as a proxy for mispricing in REITs market.

Essay 3: Despite its high profitability on average, the momentum strategy (Jegadeesh and Titman, 1993) can occasionally experience severe crashes occasionally. While previous studies often focus on market condition (Cooper, Gutierrez, and Hameed, 2004), we study the characteristics of momentum portfolios around these crashes. We show that the short leg of the momentum strategy (the portfolio of loser stocks) tend to have extreme book-to-market ratios right before crashes. This fact helps explain why momentum crashes are often driven by the sharp rebounding of the short leg component. Moreover, incorporating information on book-to-market can improve our ability to forecast momentum crashes. Our finding has two implications. First, momentum investors can improve their returns by utilizing information on stock valuation. Second, understanding what causes the extreme valuation of the short leg of momentum may shed light on the economic force behind momentum crashes.

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Essay 1:

Systematic Mispricing: Evidence from Real Estate Markets

Abstract

Despite the extensive advancement of knowledge in the field of empirical asset pricing, little is known about how this literature applies to asset classes beyond common stocks and bonds. In this paper we apply recent developments in financial economics, which posit an important role for the leverage of financial intermediaries and limited stock market participation, in understanding real estate returns. Consistent with these theories, we find that luxury consumption, funding liquidity and the capital share of income have significant explanatory power for the cross-section of equity REITs. However, this relationship is the opposite of what we expected, and the results point to a more complex set of findings that are difficult to reconcile with risk-based explanations. Our results suggest systematic mispricing of real estate assets that is heavily influenced by investor sentiment.

1. Introduction

Recent empirical studies, e.g., Adrian, Etula, and Muir (2014) and He, Kelly, Manela (2017), have shown that, in contrast with standard asset pricing models such as CAPM or the consumption-based CAPM, the intermediary asset pricing model provides a good explanation for the cross-section of expected returns for the U.S. stock market. Furthermore, He, Kelly, Manela (2017) test the intermediary asset pricing model on a wide range of asset classes, and find that the intermediary asset pricing factor has significant explanatory power for U.S. Treasury and corporate bonds, options, credit default swaps, commodities, and foreign currencies. Past attempts to apply standard asset pricing models to real estate have had mixed success. In this paper, we investigate whether a selection of limited participation models, including the intermediary asset pricing model, offer useful insights for real estate investors given the success of the models in asset classes beyond equities.

In a frictionless economy described by Lucas (1978), households can perfectly diversify away idiosyncratic risk by trading in the financial market. As a result, a household's consumption reacts only to systematic shocks to the economy; and consumption growth, which is perfectly correlated across households, provides a sufficient statistic of systematic risk that prices financial assets. While it is theoretically elegant and intuitively appealing, Lucas's consumption-based CAPM fails to a large extent to explain asset prices in empirical studies.

The failure of the standard representative-agent consumption-based CAPM is not too surprising because the real world is unlikely to be frictionless. It is difficult to perfectly diversify away idiosyncratic labor income shocks because we cannot trade human capital. While an individual can borrow (save) when there is a negative (positive) labor income shock, most households face borrowing constraints. In addition, a large fraction of U.S. households owns no

stocks, directly or indirectly. Guo (2004) incorporates these market frictions, i.e., idiosyncratic labor income shocks, borrowing constraints, and limited stock market participation, in an otherwise standard consumption-based CAPM. Guo shows that the modified *heterogeneous-agent* consumption-based CAPM provides a coherent explanation for several well-known stock market stylized facts such as the equity premium puzzle, stock market return predictability, and excess volatility puzzle.¹ In Guo's model, assets are priced by shareholders' consumption. Vissing-Jorgensen (2002) and Aït-Sahalia, Parker, and Yogo (2004) find that shareholders' consumption and luxury-goods consumption, respectively, provide a better explanation for the cross-section of stock returns than aggregate consumption. While these empirical findings are encouraging, it is a challenging task to test the limited stock market participation model empirically because it is difficult to measure the consumption of marginal shareholders who are likely to be very wealthy and underrepresented in the Consumer Expenditure Surveys used by Vissing-Jorgensen (2002).

The intermediary asset pricing model is built on the premise that a financial intermediary is the marginal investor whose "consumption" sets asset prices. For example, in He and Krishnamurthy's (2013) model, only sophisticated investors, i.e., financial intermediaries, can trade risky assets. Unsophisticated investors, i.e., households, can invest in risky assets only through a financial intermediary. While this assumption is clearly unrealistic, it might hold approximately, especially for complex assets, e.g., mortgage-backed securities and credit default swaps, and perhaps commercial real estate, which are traded mainly by sophisticated investors such as large financial intermediaries. That is, the intermediary asset pricing model is a variant of

¹ The representative-agent models by Campbell and Cochrane (1999) and Bansal and Yaron (2004) can also explain these stylized facts. However, unlike Guo (2004), these models cannot explain the unstable relation between stock market volatility and the dividend yield documented by Schwert (1989). The empirical findings by Muir (2016) also pose challenges to the representative-agent models.

the limited market participation model in which the financial intermediary's consumption growth is the priced risk factor.

In the intermediary asset pricing model, because the financial intermediary's consumption depends on its equity capital ratio or leverage, we can use shocks to the financial intermediary's equity capital ratio or leverage as the risk factor instead of using its consumption growth that is not readily observable. This feature makes the intermediary asset pricing model easy to implement empirically. Adrian, Etula, and Muir (2014) define intermediaries as broker-dealer firms and construct their leverage using the Flow of Funds data constructed by the Federal Reserve Board. They show that shocks to intermediaries price the cross-section of stock returns. He, Kelly, and Manela (2017) construct the equity capital ratio, the reciprocal of leverage, for Primary Dealer counterparties of the New York Federal Reserve. They show that their model not only explains stock market returns but also explain the returns of many other markets. Interestingly, consistent with the conjecture that participation is more segmented for more complex assets, He, Kelly, and Manela (2017) find that the intermediary asset pricing model has better explanatory power for sophisticated assets such as credit default swaps than for unsophisticated assets such as stocks.

It is important to test the intermediary asset pricing model using the real estate market for at least three reasons. First, because commercial real estate investment requires sophisticated knowledge and typically is undertaken by institutional investors rather than retail investors, it is likely that intermediary asset pricing may provide a better explanation than standard models such as CAPM or consumption-based CAPM (which are based on households). It also incorporates a role for leverage, which is commonly employed by private equity firms in purchasing commercial real estate. Second, there is an ongoing debate on the relation between the financial intermediary's equity capital ratio and asset prices. Some models, e.g., He and Krishnamurthy (2017), suggest

that the equity capital ratio is procyclical and shocks to the equity capital ratio have a positive price of risk. Empirical evidence by He, Kelly, and Manela (2017) supports this view. Other models, e.g., Adrian and Shin (2014), argue that the equity capital ratio is countercyclical and shocks to the equity capital ratio have a negative price of risk. This review is supported by empirical evidence by Adrian, Etula, and Muir (2014). Evidence from the real estate market will shed new light on this debate. Last, we compare the financial intermediary asset pricing model with the limited stock market participation model by Vissing-Jorgensen (2002) and Aït-Sahalia, Parker, and Yogo (2004). To the best of our knowledge, this test has not been done in the extant literature.

Much of the literature on real estate asset pricing has focused on equity REIT returns because of data availability and comparability to existing research methodology in financial economics. Following standard research practice established by Fama and French (1992), REITs along with other financial companies, are excluded from empirical asset pricing studies. This practice provides an opportunity to consider the extent to which recent advances in asset pricing can be applied to real estate. Furthermore, researchers have been able to exploit the unique regulatory requirements of the REIT structure to gain insight into real asset markets in a way that studies of common stocks do not permit (see Hartzell et al. 2010, Bond and Chang 2013 for discussion on this parallel markets concept)².

To preview our results, we find the financial intermediary risk factor, measures of limited stock market participation and the traditional stock market factors are all significantly priced in the cross section of real estate returns. However, the economic information contained in these factors are all subsumed by the luxury consumption factor of Aït-Sahalia, Parker and Yogo (2004).

² REITs are required to hold 75% of their assets in real property or loans secured on such assets. Further 75% of REIT annual gross income must be from real estate related sources. Also important is the requirement that a REIT distribute 90% of its taxable income, which limits the ability to retain earnings within the organization.

This finding is robust to alternative definitions of luxury consumption or proxies for shareholder consumption. Surprisingly, the sign of all these risk factors is the opposite of that expected, which suggests a negative price for risk. Our explanation for this finding is that the REIT market is driven by sentiment. When sentiment is strong, stocks with lower past returns, low returns on assets, and negative earnings surprises are overvalued compared with stocks with high past returns, high returns on assets and positive earnings surprises. The mispricing is corrected when the sentiment subsides. Our findings are consistent with an extensive literature on real estate returns that points to sentiment as being a pervasive factor. This finding also accords with recent work by Stambaugh and Yuan (2017) on mispricing in the stock market.

Section 2 reviews the related literature. Section 3 describes the methodology used to construct the main variables in our study along with the data selected. Section 4 discusses our empirical results and section 5 concludes.

2. Related literature on REITs

The literature on REIT asset pricing literature has greatly expanded in recent years. Bond and Xue (2016) apply the investment based asset pricing model to the REIT market. They show the importance of profitability and investment factors in both the time series and cross section of returns. Van Nieuwerburg (2018) considers the exposure to stock and bond factors in the time series of real estate returns. He also studies the HKM factor in the time series of REIT returns and finds that it provides little explanation for returns beyond that of a five-factor model.

Another set of literature has developed since the financial crisis that considers the tail-risk of financial markets as a risk factor. Van Nieuwerburg examines the probability of disaster from Siriwardane (2015) and the financial fragility factor of Giglio, Kelly and Pruitt (2016) and finds

that REITs load positively on this factor although the effect is reduced when standard factors such as size, value and momentum are included. Alcock and Andrilikova (2018) shows that a measure of asymmetric dependence is priced in the cross section of REIT returns. In a contemporary paper, Boudry, Connolly and Steiner (2018) show that REITs offer a hedge against the flight to safety risk of Baele et al. (2014).

A final related development in real estate asset pricing points to the role of sentiment as an important factor beyond traditional risk-based explanations for asset returns. Early work by Clayton and McKinnon (2003), and Gentry, Jones and Mayer (2004) extended the literature on sentiment in closed-end fund discounts to REIT pricing relative to net asset value. Ling, Naranjo and Scheik (2014) find a positive relationship between measures of investor sentiment for private real estate markets and subsequent period real estate returns. However, long-horizon regressions show this sentiment is associated with possible mispricing. Das et al. (2015) show that the sentiment of institutional investors “spills over” from private real estate markets to public markets and highlights the role of economic conditions in determining the direction of this spillover.

3. Methodology and Data

The sample used in this paper consists of all equity REITs listed in CRSP/Ziman database. The sample includes 436 distinct REITs traded on the NYSE, Amex, and Nasdaq exchanges from 1987 to 2016. From 1987 to 2016, the market capitalization of all equity REITs grew from 8.5 billion dollars to one trillion dollars and the number of REITs each year grow from 87 to 188. Data on REIT returns are from CRSP and the accounting data are from COMPUSTAT. Following Fama and French (1992), we construct REIT-based versions of the Fama-French factors. Following Hou, Xue, and Zhang (2015), we construct REITs-based investment and profitability factors. The

macroeconomic factors used in this paper are from the FRED database hosted by the Federal Reserve Bank of St. Louis.

We construct the intermediary asset pricing factors following Adrian, Etula, and Muir (2014) and He, Kelly, Manela (2017). HKM is the He, Kelly, and Manela (2017) market capital ratio factor defined as the ratio of total market equity to total market assets (book debts plus market equity) of primary dealer holding companies. AEM is the Adrian, Etula, and Muir (2014) leverage ratio factor and is defined as the ratio of total financial assets to the difference between total financial assets and total liabilities of brokers and dealers. We investigate whether these two intermediary asset pricing factors are priced in the cross-section of expected returns on real estate assets. For comparison, we construct limited participation factors. LUXCON is the year-over-year log changes in luxury sales that we construct following Aït-Sahalia, Parker, and Yogo (2004). Δ SHCON is Shareholders' consumption growth following Malloy, Moskowitz, and Vissing-Jorgensen (2009). Δ CS4 is year-over-year changes in capital shares proposed by Lettau, Ludvigson, and Ma (2018). Full descriptions of our data construction methods are provided in the appendix.

Table 1 reports summary statistics for the main risk factors that we consider in the paper over the 1987Q1 to 2016Q4 period. MKT is the excess stock market return. REIT is the excess REIT market return. Δ DEF is the change in the default spread. Δ DIV is the change in the aggregate REIT dividend price ratio. SMB, HML, RMW, and CMA are the Fama and French factors. SMB is the return difference between small and large capitalization stocks. HML is the return difference between high and low book-to-market equity ratio stocks. RMW is the return difference between high and low profitability stocks. CMA is the return difference between low and high asset growth stocks. Luxury consumption growth has a higher mean and higher volatile than shareholder consumption growth, and the correlation between the two series is as low as 0.065. The two

financial intermediary factors HKM and AEM also have a low correlation, as HKM is constructed by using the market value of assets and AEM is constructed by using the book value of assets.

Table 2 reports the summary statistics of return differences on REIT hedging portfolios. At the beginning of each month, we sort all equity REITs into five portfolios based on SIZE (market capitalization), BM (book-to-market ratio), MOM (past returns), AG (asset growth), ROE (return on equity), and SUE (earning surprises). We calculate the value-weighted portfolio return and take the return difference between the first and fifth quintiles. Consistent with Chui et al. (2003a, b), Price et al. (2012), and Bond and Xue (2017), we find that MOM, ROE, and SUE are significantly positive. SIZE, BM, and AG are positively but economically small and statistically insignificant. There is a strong positive correlation between MOM, ROE and SUE. The REIT hedging portfolios also correlate with their common stock counterparts, the correlation coefficients are 0.13, 0.28, 0.56, 0.19, and 0.36 for SIZE, BM, MOM, AG, and ROE, respectively (untabulated).

4. Cross-sectional test

4.1 Financial Intermediary Models

In Table 3, we report the univariate Fama and MacBeth (1973) cross-sectional regression results. For each risk factor, we test the univariate model in the cross-section of 30 portfolios. The 30 test portfolios consist of six groups of quintile portfolios formed on size, book-to-market, momentum, asset growth, return on equity and earnings surprises. We first estimate the betas from the time-series regression of 30 portfolios excess return, and then run the cross-sectional regression of the excess portfolio returns on the estimated betas. We report the estimated risk price and its standard errors in Table 3. The Fama and MacBeth (1973) standard error and the Shanken (1992) corrected standard error are in parentheses and brackets, respectively.

He and Krishnamurthy (2013) argue that a decrease in primary dealers' equity, for example, during the 2008 financial crisis, increases the marginal utility of primary dealers who are the marginal investors. If an asset performs poorly when primary dealers' equity decrease, it should have a positive risk premium. Consistent with this theoretical implication, He, Kelly, and Manela (2017) find that the aggregate capital equity ratio factor, HKM, carries a positive risk price for many asset classes. We find HKM is significantly priced at the 5% level for REIT portfolios; however, its estimated risk price is *negative*. The puzzling result reflects the fact that while MOM, ROE, and SUE are significantly positive, they correlate negatively with HKM (Table 2). In particular, Figure 1 shows that HKM decreases drastically in 2008Q4, while MOM is about 22%. Results are similar for ROE and SUE (untabulated).

Adrian, Etula, and Muir (2014) argue that a decrease in brokers and dealers' leverage, for example, during 2008 financial crisis, indicates tighter funding liquidity. Assets that do poorly when leverage decreases thus require a positive risk premium. Consistent with this implication, Adrian, Etula, and Muir (2014) find that the AEM factor has a significantly positive risk price for common stock portfolios. In contrast with their findings, Table 3 shows that the risk price of AEM is negative albeit statistically insignificant for REIT portfolios. The puzzling result reflects the fact that while MOM, ROE, and SUE are significantly positive, they correlate negatively with AEM (untabulated). For example, Figure 2 shows that AEM decreases drastically in 2008Q4, while MOM is about 22%.

4.2 Limited Stock Market Participation Models

Our results suggest that financial intermediary asset pricing models do not explain the cross-section of REIT returns. One possibility is that financial intermediaries are not the marginal

investors of REIT assets. We explore whether limited stock market participation models explain the cross-section of REIT returns. We consider three measures of limited stock market participation risk factors. The first factor is luxury consumption growth. Because it exhibits strong cyclical variation, we use the year-over-year growth. For example, for 2000Q1, LUXCON is the percentage change in luxury consumption between 2000Q1 and 1999Q1. We estimate loadings in two ways. First, we regress quarterly portfolio returns of 2000Q1 on LUXCON of 2000Q1 and this is the specification LUXCON in Table 3. Second, we regress portfolio returns over 1999Q2 to 2000Q1 on LUXCON of 2000Q1, and this is the specification of LUXCON4. As a robustness check, we also construct LUXCON8, as the growth ratio from 1998Q1 to 2000Q1, and use the returns over the 1998Q2 to 2000Q1 to estimate loadings. This is the specification LUXCON8. We find that luxury consumption growth is significantly priced and accounts for a large variation (for example, 60% for LUXCON) of the cross-section of REIT portfolio returns. However, contrary to the prediction of limited participation theory, its risk price is negative.

The second limited stock market participation risk factor is the change in the capital share of income proposed by Lettau, Ludvigson, and Ma (2018). Because top shareholders finance their consumption primarily out of capital income, change in the capital share of income is likely to track top shareholders' consumption growth closely. As in Lettau, Ludvigson, and Ma (2018), we use the year-over-year change, $\Delta CS4$, and estimate loadings using the return over the corresponding four quarters period. Table 3 shows that contrary to the implication of limited stock market participation theory, the risk price is *negative* albeit statistically insignificant.

The last limited stock market participation risk factor is shareholders' consumption growth, $\Delta SHCON$. We follow Malloy, Moskowitz, and Vissing-Jorgensen (2009) and construct this

variable using data from the Consumption Expenditure Survey. Table 3 shows that the risk price of ΔSHCON is positive, albeit statistically insignificant at the 10% level.

4.3 Other Risk Factors

In Table 3, we also consider commonly used risk factors. In the CAPM, loadings on excess market returns explains the cross-section of stock returns. We use MKT (excess stock market returns) and REIT (excess REIT market returns) as proxies for excess market returns. We find that contrary to CAPM, the risk price is significantly *negative* for both MKT and REIT. The risk price of excess Treasury bond returns is positive and marginally significant; however, it accounts for less than 40% of the cross-section of expected REIT portfolio returns. Untabulated results show that the explanatory power of the excess Treasury bond return vanishes when we control for loadings on MKT or REIT. Last, the risk price of excess corporate bond returns is positive albeit statistically insignificant at the 10% level.

REIT companies have high leverage, and their performance is significantly affected by interest rate changes. TED is the spread between the 3-month LIBOR rate and the 3-month Treasury rate. DEF is the credit spread between BAA and Aaa-rated corporate bonds. An increase in these variables indicate an increase in borrowing costs. An asset that performs poorly when funding costs increase should have a positive risk premium. Contrary to this conventional wisdom, we find that risk price is positive for both ΔTED and ΔDEF . We also consider the stochastically detrended risk-free rate (ΔRREL) and the spread between the long-term and short-term Treasury bonds (ΔTERM). Neither variable has a significant risk price, however.

Because investors are risk averse, an increase in stock market variance corresponds to a deterioration in investment opportunities. Consistent with this conjecture, Ang, Hodrick, Xing,

and Zhang (2006) show that stocks with higher loadings on changes in stock market variance have lower expected returns. As in Ang, Hodrick, Xing, and Zhang (2006), we measure stock market variance using options-implied variance. However, we find that changes in stock market variance, ΔMV , has a significantly positive price of risk.

In Campbell's (1993) ICAPM, risk factors are state variables that forecast stock market returns. Campbell (1996) includes the aggregate dividend price ratio as a risk factor, because of its predictive power for excess stock market returns. In Table 3, ΔDIV is the change in the aggregate REIT dividend price ratio. We find that it is significantly priced with a positive price of risk. However, because ΔDIV has a strong negative correlation with REIT, untabulated results show that its explanatory power becomes insignificant when we control for loadings on REIT in the cross-sectional regression.

Lastly, we consider Fama and French risk factors and the momentum factor constructed using common stocks in univariate regressions. We find that MOM and RMW have significantly positive risk prices. The results reflect the fact that REIT momentum, profitability premium, and SUE correlate positively with MOM or RMW. We will discuss the multivariate regression results using common stock risk factors in Table 5.

4.4 Multivariate Cross-Sectional Regressions

We find that many risk factors are significantly priced in the univariate Fama and MacBeth (1973) regression. In Table 4, we compare their explanatory power in multivariate regressions. Column 1 shows that REIT subsumes the information content of MKT in explaining the cross-section of REIT portfolio returns. Untabulated results show that REIT drives out other risk factors except ΔDEF and LUXCON. Column 2 shows that REIT and ΔDEF have similar

explanatory power, and column 3 shows that LUXCON drives out REIT. Columns 4, 5, and 6 show that LUXCON drives out ΔDEF , ΔDIV and HKM.

Our results seem to suggest that MKT, REIT, ΔDEF , ΔDIV , and HKM have similar explanatory power for REIT portfolio returns. They have relatively weak explanatory power possibly because of measurement errors. We address this issue in two ways. First, we also construct the first-principle component of these factors, FPC. Column 9 shows that FPC is only marginally significant in the bivariate regression, while LUXCON is statistically significant at the 1% level. Second, we construct tracking portfolios for both HKM and LUXCON. We regress HKM or LUXCON on a constant and two extreme REIT portfolios of each characteristic, and use the fitted value as the risk factor. Column 10 shows that the results with tracking risk factors are similar to those reported in column 9. Overall, our results suggest that LUXCON is a strong explanatory variable for the cross-section of REIT portfolio returns.

In Table 5, we compare LUXCON with common stock risk factors. Column 1 reports the results of the Fama and French (1993) three-factor model. Column 2 reports the Fama and French three-factor model augmented by the momentum factor. Column 3 reports the Fama and French (2015) five-factor models. We control for LUXCON in columns 4, 5, and 6 and find that the common stock risk factors become insignificant, while LUXCON is statistically significant at the 1% level.

In Table 6, we compare LUXCON with risk factors constructed using REIT portfolios. In column 1, the three-factor model (REIT, SIZE, and BM) accounts for 53% of cross-sectional variation in REIT portfolio returns. When we add LUXCON as a risk factor, the R^2 increases to 72%, and LUXCON is statistically significant at the 1% level (column 2). For the four-factor model (REIT, SIZE, BM, and MOM) in column, the R^2 is about 72%, and MOM is

significant at the 1% level. Column 4 shows that LUXCON is significant at the 5% level when controlling for the four factors. Column 5 shows that the five-factor model (REIT, SIZE, BM, AG, and ROE) has good explanatory power for the cross-section of REIT portfolio returns, with an R^2 of 78%. This result is hardly surprising because the risk factors are constructed using the testing REIT portfolios. In addition, column 6 shows that the explanatory power of LUXCON becomes statistically insignificant when controlling for the five factors. However, when we use the tracking portfolio for LUXCON, its explanatory power is significant at the 1% level, even when we control for the five factors (column 7). Overall, our results suggest that LUXCON, a macrovariable, does have a significant relation with the cross-section of REIT portfolio returns.

4.5 Alternative Measures of Luxury Consumption

Table 7 reports alternative measures of luxury consumption. These consumption measures are personal consumption and expenditure data from the Bureau of Economic Analysis. JW is consumption growth on Jewelry and Watches. BA is consumption growth on boats and aircrafts. The risk price of BA and JW is significantly negative at the 10% level. NDS is consumption growth on nondurable goods and services. Interestingly, the risk price of NDS is also significantly negative at the 10% level. When we compare the explanatory power of these alternative measures to LUXCON, LUXCON remain significant.

4.6 Systematic Risk Factor or Systematic Mispricing Factor?

We find that financial intermediary risk factors, limited stock market participation risk factors, CAPM risk factors, credit market risk factors, and ICAPM risk factors are significantly priced in the cross-section of REIT portfolio returns. In addition, their information content is

subsumed by that of LUXCON. Our result suggests that LUXCON is a pervasive systematic factor in the REIT market. However, the risk prices of these factors have the opposite signs to those stipulated by the theories that motivate them. It is very difficult to reconcile our results with a risk-based explanation. It is very hard to understand why a hedging portfolio that performs well during the financial crisis should have a high expected return. In this Section, we explore the hypothesis that our results reflect systematic mispricing.

The hypothesis is that the REIT market is influenced by investor sentiment. When sentiment is strong, stocks with lower past returns, low returns on assets, and negative earnings surprises (hereafter we refer to these stocks as weak stocks) are overvalued compared with stocks with high past returns, high returns on assets and positive earnings surprises (hereafter we refer to these stocks as robust stocks). The mispricing is corrected when sentiment subsides. Stambaugh and Yuan (2017) use this hypothesis to explain systematic mispricing in common stocks. However, there is an interesting difference between sentiment in the common stock market and sentiment in REITs. Stambaugh and Yuan show that the Baker and Wurgler (2006) sentiment measure, which is orthogonal to business cycle variables, is priced in common stocks. Our results suggest that REIT market sentiment has a strong comovement with business cycles.

Our hypothesis has the following implications. First, weak stocks have stronger comovement with sentiment than robust stocks. This explains why weak stocks have lower average returns than robust stocks, because the former is more susceptible to overpricing. Second, MOM, ROE, and SUE have higher returns mainly during the period when sentiment decreases. Third, with the increase in the share of institutional investors in the REIT market over our sample, the explanatory power of sentiment for REIT has become weaker. Our results are consistent with these implications.

We find that standard measures of business cycles, e.g., industrial production and the Chicago Fed National Activity index are negatively priced in the cross-section of REITs, and their information content is subsumed by LUXCON (Table 7). This result indicates that sentiment in the REIT market is strongly procyclical. Furthermore, standard sentiment measures, such as the Michigan survey, OECD, Conference Board, a housing market index, and house start permits are negatively priced, and their information content is similar to that of LUXCON (Table 8). Interestingly, the Baker and Wurgler sentiment measure is not priced (Untabulated). Table 9 shows that MOM, ROE and SUE are positive only in quarters of the lowest ΔCCI quartile. This result indicates that the short leg of MOM, ROE and SUE are less mispriced when sentiment is low. Table 10 shows that the explanatory power of LUXCON is stronger in the early sample spanning 1987Q1 to 2007Q4 period, and it decreases substantially in the post-1994 period as more institutional investors enter the REIT market.

5. Conclusion

This paper considers the question of asset pricing in real estate markets. We provide a detailed analysis of the cross section of REIT returns. Our results are based on models of limited market participation and include the recent work on financial intermediaries, as well as shareholder consumption models. We find that the market return, REIT market return, the default spread, dividend yield growth, capital ratio, and luxury consumption growth have significant explanatory power for cross-sectional REIT returns. Luxury consumption growth subsumes the information content of all the other factors. This finding is robust to time period and alternative definitions of luxury consumption.

Another finding is that unlike the results for common stocks, the risk price associated with these factors is negative, which does not appear to be consistent with standard economic intuition. However, our explanation of this result is that real estate markets are heavily influenced by investor sentiment. This sentiment also has strong comovement with the business cycle. One implication is the weak REITs (REITs with low past returns, low return on assets and negative earnings surprises) get bid up in price relative to robust REITs. Eventually this mispricing is corrected when sentiment subsides.

Figure 1. Capital Ratio Factor and Momentum Factor Returns, 1987-2016. The solid line is the He, Kelly, and Manela (2017) market capital ratio factor defined as the ratio of total market equity to total market assets (book debts plus market equity) of primary dealer holding companies. The Dashed line is the momentum factor constructed using REIT data. Quintile momentum portfolios are sorted on the past two to 12 month aggregate returns.

Figure 2. Leverage Ratio Factor and Momentum Factor Returns, 1987-2016. The solid line is the Adrian, Etula, and Muir (2014) leverage ratio factor and is defined as the ratio of total financial assets to the difference between total financial assets and total liabilities of brokers and dealers. The Dashed line is the momentum factor constructed using REIT data. Quintile momentum portfolios are sorted on the past two to 12 month aggregate returns.

Table 1
Descriptive Statistics

Panel A list the time series average of factor means and standard deviations. Panel B lists the time series correlations. HKM is the market equity capital ratio factor of NY Fed primary dealers by He, Kelly, and Manela (JFE, 2017). AEM is the leverage ratio factor by Adrian, Etula, and Muir (JF, 2014). Δ LUXCON is the year-over-year log change in luxury sales by Aït-Sahalia, Parker, and Yogo (JF, 2004). SHCON is Shareholders' consumption growth by Malloy, Moskowitz, and Vissing-Jorgensen (JF, 2009). Δ CS4 is the year-over-year change in capital share by Lettau, Ludvigson, and Ma (2018). MKT is excess stock market returns. REIT is excess REIT market returns. Δ DEF is the change in default spread. Δ DIV is the change in REIT dividend yield. SMB is the return difference between small and large capitalization stocks. HML is the return difference between high and low book-to-market equity ratio stocks. RMW is the return difference between high and low profitability stocks. CMA is the return difference between low and high asset-growth stocks.

	HKM	AEM	LUXCON	SHCON	Δ CS4	MKT	REIT	Δ DEF	Δ DIV	SMB	HML	RMW	CMA
Panel A: Summary Statistics													
Mean	0.014	0.001	0.081	0.005	0.003	0.020	0.020	-0.000	-0.000	0.004	0.007	0.010	0.009
SD	0.126	0.072	0.124	0.043	0.015	0.084	0.095	0.002	0.009	0.048	0.059	0.048	0.041
Panel B: Cross-Correlations													
HKM	1.000												
AEM	-0.075	1.000											
LUXCON	0.135	0.161	1.000										
SHCON	-0.011	-0.014	0.065	1.000									
Δ CS4	0.092	-0.046	-0.107	0.055	1.000								
MKT	0.754	-0.060	0.220	-0.082	0.081	1.000							
REIT	0.570	0.156	0.100	-0.017	0.130	0.607	1.000						
Δ DEF	-0.471	-0.276	-0.064	-0.002	-0.178	-0.382	-0.496	1.000					
Δ DIV	-0.541	-0.021	-0.042	-0.004	-0.069	-0.505	-0.814	0.384	1.000				
SMB	0.361	0.051	-0.076	0.004	0.132	0.340	0.471	-0.197	-0.418	1.000			
HML	0.178	0.275	-0.023	0.004	-0.004	-0.203	0.307	-0.181	-0.274	0.109	1.000		
RMW	-0.357	0.002	-0.251	0.012	0.039	-0.529	-0.194	0.206	0.058	-0.243	0.356	1.000	
CMA	-0.116	0.132	-0.033	-0.081	-0.002	-0.319	0.092	0.002	-0.028	-0.000	0.719	0.351	1.000

Table 2
REIT Hedging Portfolios

Panel A lists the time series average of factor means and standard deviations based the sample of equity REITs from 1987 to 2016. Panel B lists the time series correlations. REIT_MKT is excess REIT market returns. SMB is the return difference between portfolios of small capitalization and large capitalization REITs. HML is the return difference between value and growth portfolios. MOM is the return difference between winner and loser portfolios. AG is the return difference between high asset-growth and low asset-growth portfolios. ROE is the return difference between high profitability and low profitability portfolios. SUE is the return difference between portfolios with high earning surprise and low earning surprise. HKM is the market equity capital ratio factor of NY Fed primary dealers by He, Kelly, and Manela (JFE, 2017). LUXCON is the year-over-year log changes in luxury goods sales by Ait-Sahalia, Parker, and Yogo (JF, 2004). ΔCCI is the change in consumer confidence index from Conference Board dataset.

	REIT	SIZE	BM	MOM	AG	ROE	SUE	HKM	LUXCO N	ΔCC I
Mean	0.020	0.003	0.006	0.021	0.006	0.026	0.030	0.014	0.081	0.002
t-value	2.347	0.399	0.763	2.042	1.207	3.099	5.135	0.126	0.124	0.147
REIT_MK T	1.000									
SIZE	-0.252	1.000								
BM	0.337	0.439	1.000							
MOM	-0.417	-0.161	-0.491	1.000						
AG	-0.129	0.212	0.286	-0.003	1.000					
ROE	-0.290	-0.372	-0.659	0.647	-0.229	1.000				
SUE	-0.273	-0.241	-0.415	0.653	-0.100	0.677	1.000			
HKM	0.570	-0.073	0.349	-0.390	-0.026	-0.335	-0.220	1.000		
LUXCON	0.100	-0.021	-0.044	-0.081	-0.036	-0.169	-0.128	0.134	1.000	
ΔCCI	0.466	-0.130	0.199	-0.527	0.140	-0.466	-0.423	0.533	0.214	1.000

Table 3
Univariate Cross-Sectional Regressions

This table shows the univariate cross-sectional regression results for all factors. The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. The independent variables are: Treasury bond return (TB), corporate bond return (CB), change in TED spread (Δ TED), change in stochastically detrended risk-free rate (Δ RREL), change in the term spread (Δ TERM), change in market variance (Δ MV). We follow Lettau, Ludvigson, and Ma (2018) to construct capital share growth (Δ CS4). HKM is the market equity capital ratio factor of NY Fed primary dealers by He, Kelly, and Manela (JFE, 2017). AEM is the leverage ratio factor by Adrian, Etula, and Muir (JF, 2014). We use different horizons to test the luxury consumption growth factor. LUXCON: we regress quarterly returns on quarterly luxury consumption growth to estimate beta. LUXCON4: we regress four-quarter returns on quarterly luxury consumption growth to estimate beta. LUXCON8: we estimate beta using two-year changes in luxury consumption and returns over two years. For each risk factor, we report the estimated risk price and its standard errors. The Fama and MacBeth (1973) standard error is in parentheses and the Shanken (1992) error is in brackets.

	Constant	Coefficient	R^2		Constant	Coefficient	R^2
MKT	0.047 (4.923) [4.463]	-0.039 (-2.379) [-2.199]	0.378	AEM	0.028 (3.123) [2.800]	-0.036 (-1.537) [-1.389]	0.125
REIT	0.060 (4.671) [4.308]	-0.040 (-2.511) [-2.369]	0.421	LUXCO N	0.035 (4.326) [2.432]	-0.183 (-3.952) [-2.269]	0.603
TB	0.025 (3.093) [2.774]	0.027 (2.124) [1.935]	0.368	LUXCO N4	0.038 (4.598) [4.399]	-0.038 (-2.801) [-2.764]	0.539
CB	0.017 (1.881) [1.825]	0.012 (0.898) [0.874]	0.029	LUXCO N8	0.036 (4.193) [4.127]	-0.004 (-2.430) [-2.451]	0.376
Δ TED	0.026 (3.380) [3.065]	0.001 (1.734) [1.489]	0.237	SHCON	0.020 (2.423) [2.297]	0.014 (0.761) [0.723]	0.025
Δ RREL	0.020 (2.322) [2.063]	-0.018a (-1.516) [-1.357]	0.097	Δ CS4	0.028 (3.456) [3.378]	-0.003 (-1.667) [-1.648]	0.182
Δ DEF	0.043 (4.753) [4.301]	0.001 (2.433) [2.247]	0.491	SMB	0.040 (4.096) [3.761]	-0.021 (-2.069) [-1.929]	0.359
Δ TERM	0.021 (2.517) [2.203]	-0.003 (-1.566) [-1.381]	0.184	HML	0.034 (3.655) [3.320]	-0.027 (-1.781) [-1.635]	0.252
Δ DIV	0.048 (4.880) [4.574]	0.003 (2.351) [2.250]	0.358	MOM	0.034 (4.369) [4.071]	0.032 (2.297) [2.183]	0.425
Δ MV	0.040 (4.713) [4.279]	0.003 (2.166) [1.999]	0.321	RMW	0.031 (4.041) [3.463]	0.029 (2.255) [1.963]	0.332
HKM	0.044 (4.640) [4.243]	-0.056 (-2.257) [-2.101]	0.400	CMA	0.023 (2.630) [2.513]	-0.013 (-0.872) [-0.835]	0.045

Table 4
Multivariate Cross-Sectional Regressions

This table shows the multivariate cross-sectional regression results on selected factors (these factors have significant explanatory power on the cross-sectional return in the univariate regressions in table 3). The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. MKT is excess stock market returns. REIT is excess REIT market returns. Δ DEF is the change in the default spread. Δ DIV is the change in REIT dividend yields. HKM is the market equity capital ratio factor of NY Fed primary dealers by He, Kelly, and Manela (JFE, 2017). Δ LUXCON is the year-over-year log change in luxury sales by Aït-Sahalia, Parker, and Yogo (JF, 2004). FPC: the first principle component of MKT, REIT, Δ DEF, Δ DIV, HKM. Column 10 shows the regression result using tracking portfolios: we regress HKM and LUXCON on r1, r5, r6, r10..., r26, r30, and use the fitted values, F1 and F2, respectively, as the risk factors. The Fama and MacBeth (1973) standard error is in parentheses and the Shanken (1992) error is in brackets.

	1	2	3	4	5	6	7	8	9	10
Constant	0.061 (4.708) [4.315]	0.045 (3.903) [3.554]	0.053 (4.352) [2.805]	0.043 (4.762) [4.200]	0.047 (4.832) [3.046]	0.043 (4.564) [2.907]	0.048 (4.103) [2.742]	0.057 (4.193) [2.645]	0.047 (3.566) [2.956]	0.043 (4.519) [3.930]
MKT	-0.019 (-1.014) [-0.943]									
REIT	-0.041 (-2.605) [-2.448]	-0.024 (-1.696) [-1.595]	-0.032 (-2.112) [-1.512]				-0.027 (-1.887) [-1.408]	-0.037 (-2.290) [-1.588]		
Δ DEF		0.001 (1.864) [1.718]		0.078 (1.648) [1.181]			0.066 (1.083) [0.753]			
Δ DIV					0.002 (1.713) [1.234]					
HKM						-0.046 (-1.913) [-1.309]		-0.025 (-0.659) [-0.428]		-0.020 (-2.029) [-1.894]
FPC									-0.349 (-2.317) [-1.691]	
LUXCON			-0.145 (-4.316) [-2.881]	-0.133 (-4.175) [-2.908]	-0.151 (-4.404) [-2.873]	-0.148 (-4.624) [-3.062]	-0.136 (-4.104) [-2.836]	-0.148 (-4.624) [-3.033]	-0.145 (-4.478) [-3.009]	-0.022 (-5.092) [-4.846]
R^2	0.422	0.491	0.693	0.696	0.687	0.669	0.700	0.698	0.685	0.775

Table 5**Multivariate Cross-Sectional Regressions with Common Stock Factors**

This table shows the multivariate cross-sectional regression results using common stock risk factors and the luxury consumption risk factor. The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. SMB, HML, RMW, CMA and MKT are the Fama-French five factors. The Fama and MacBeth (1973) standard error is in parentheses and the Shanken (1992) error is in brackets.

	1	2	3	4	5	6
Constant	0.047 (4.910) [4.608]	0.038 (3.697) [3.458]	0.044 (4.570) [3.242]	0.045 (4.799) [2.775]	0.041 (3.952) [2.377]	0.045 (4.682) [2.867]
MKT	-0.028 (-1.862) [-1.776]	-0.020 (-1.449) [-1.383]	-0.029 (-1.974) [-1.508]	-0.031 (-2.045) [-1.301]	-0.026 (-1.919) [-1.288]	-0.030 (-2.066) [-1.390]
SMB	-0.011 (-1.136) [-1.080]	-0.008 (-0.821) [-0.777]	-0.017 (-1.799) [-1.354]	0.012 (1.196) [0.738]	0.013 (1.218) [0.775]	0.005 (0.544) [0.364]
HML	-0.003 (-0.261) [-0.247]	0.002 (0.109) [0.103]	0.005 (0.407) [0.301]	-0.015 (-1.117) [-0.683]	-0.012 (-0.884) [-0.559]	-0.010 (-0.748) [-0.484]
MOM		0.003 (2.101) [2.005]			-0.006 (-0.457) [-0.312]	
RMW			0.018 (2.060) [1.566]			0.014 (1.637) [1.097]
CMA			0.029 (2.470) [1.796]			0.010 (0.896) [0.569]
LUXCON				-0.168 (-4.724) [-2.830]	-0.158 (-4.919) [-3.084]	-0.146 (-4.645) [-2.969]
R^2	0.408	0.435	0.529	0.695	0.702	0.725

Table 6**Multivariate Cross-Sectional Regressions with REITs Factors**

This table shows the multivariate cross-sectional regression results on factors constructed using REITs stocks. The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. SMB is return difference between small and large capitalization REIT portfolios. HML is the return difference between high and low book-to-market ratio REIT portfolios. MOM is the return difference between winner and loser REIT portfolios. AG is the return difference between high investment and low investment REIT portfolios, and ROE is the return difference between high profitability and low profitability REIT portfolios. The Fama and MacBeth (1973) standard error is in parentheses and the Shanken (1992) error is in brackets.

	1	2	3	4	5	6	7
Constant	0.080 (5.136) [4.165]	0.006 (4.294) [2.832]	0.039 (2.362) [2.232]	0.048 (2.927) [2.082]	0.031 (1.782) [1.602]	0.034 (1.912) [1.699]	0.040 (2.369) [2.086]
REIT	-0.060 (-3.355) [-2.837]	-0.044 (-2.529) [-1.799]	-0.018 (-0.992) [-0.949]	-0.027 (-1.479) [-1.114]	-0.011 (-0.547) [-0.501]	-0.014 (-0.696) [-0.630]	-0.020 (-1.036) [-0.935]
SIZE	0.002 (0.236) [0.235]	0.003 (0.436) [0.430]	0.001 (0.181) [0.181]	0.003 (0.393) [0.389]	0.003 (0.358) [0.358]	0.003 (0.377) [0.376]	0.003 (0.406) [0.405]
BM	-0.004 (-0.480) [-0.467]	-0.001 (-0.140) [-0.135]	0.001 (0.068) [0.068]	-0.002 (-0.267) [-0.261]	-0.004 (-0.575) [-0.573]	-0.004 (-0.537) [-0.534]	-0.003 (-0.455) [-0.453]
MOM			0.032 (3.020) [3.009]	0.027 (2.553) [2.082]			
AG					0.007 (1.392) [1.380]	0.008 (1.421) [1.407]	0.008 (1.492) [1.477]
ROE					0.029 (3.278) [3.254]	0.028 (3.251) [3.225]	0.030 (3.407) [3.379]
LUXCON		-0.133 (-4.094) [-2.799]		-0.119 (-3.611) [-2.648]		-0.004 (-0.975) [-0.537]	-0.021 (-4.283) [-4.032]
R^2	0.532	0.721	0.595	0.731	0.775	0.777	0.791

Table 7**Cross-Sectional Regressions with Alternative Luxury Consumption and Aggregate Economic Activity factors**

This table shows the multivariate cross-sectional regression results using alternative luxury consumption and aggregate economic activity factors. The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. NDS is non-durable and service consumption growth from PCE database. JW is jewelry and watch consumption growth from PCE database. BA is boats and aircraft consumption growth from PCE database. ΔIP is Industrial production growth from Federal Reserve Bank of St. Louis. $\Delta CFNAI$ is Chicago Fed National Activity Index. The Fama and MacBeth (1973) standard error is in parentheses and the Shanken (1992) error is in brackets.

	1	2	3	4	5	6	7	8	9	10
Constant	0.028 (3.453) [2.472]	0.034 (4.307) [2.396]	0.035 (4.041) [3.325]	0.039 (4.495) [2.672]	0.039 (5.156) [4.303]	0.045 (5.820) [3.245]	0.038 (4.660) [3.186]	0.038 (4.725) [2.864]	0.033 (4.217) [3.769]	0.037 (4.686) [3.148]
NDS	-0.004 (-2.476) [-1.796]	-0.004 (-2.367) [-1.341]								
JW			-0.019 (-2.290) [-1.913]	-0.021 (-2.543) [-1.557]						
BA					-0.037 (-3.003) [-2.575]	-0.041 (-3.193) [-1.886]				
ΔIP							-0.015 (-2.913) [-2.026]	-0.015 (-2.972) [-1.839]		
$\Delta CFNAI$									-0.224 (-2.408) [-2.195]	-0.140 (-1.450) [-1.025]
LUXCON		-0.186 (-4.346) [-2.478]		-0.165 (-4.367) [-2.669]		-0.179 (-3.919) [-2.233]		-0.154 (-4.338) [-2.720]		-0.134 (-3.968) [-2.753]
R^2	0.320	0.605	0.365	0.655	0.213	0.678	0.568	0.665	0.486	0.679

Table 8
Cross-Sectional Regressions with Consumer Sentiment Measures

This table shows the multivariate cross-sectional regression results using alternative measure of sentiment. The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. MICHIGAN is consumer sentiment index published by University of Michigan. OECD is The Organization for Economic Co-operation and Development sentiment measure. CCI is a measure of sentiment published by the Conference Board. HMI is NAHB Wells Fargo National house market index from National Association of Home builders. PERMIT4 is the annual change in US new home building permits from the Department of Housing and Urban Development. LUXCON is luxury consumption growth. LUXCON4 is the four-quarter growth in luxury consumption. The Fama and MacBeth (1973) standard error is in parentheses and the Shanken (1992) error is in brackets.

	1	2	3	4	5	6	7	8	9	10	11
CON	0.051 (4.965) [4.122]	0.042 (4.744) [3.274]	0.039 (4.281) [4.124]	0.044 (4.827) [4.185]	0.043 (4.599) [3.172]	0.037 (4.053) [3.881]	0.0268 (4.460) [4.105]	0.039 (4.749) [3.171]	0.034 (3.415) [3.228]	0.048 (4.528) [4.381]	0.037 (3.621) [3.459]
MICHIGAN	-0.043 (-2.579) [-2.337]	-0.031 (-1.771) [-1.287]	-0.012 (-0.957) [-0.745]								
OECD				-0.003 (-2.611) [-2.314]	-0.002 (-1.818) [-1.307]	-0.001 (-0.881) [-0.868]					
HMI							-0.066 (-2.332) [-2.189]	-0.029 (-0.985) [-0.707]	0.006 (0.157) [0.153]		
PERMIT4										-0.052 (-2.475) [-2.454]	-0.022 (-1.456) [-1.139]
LUXCON		-0.126 (-3.770) [-2.685]			-0.125 (-3.592) [-2.549]			-0.136 (-4.211) [-2.913]			
LUXCON4			-0.035 (-3.275) [-3.297]			-0.038 (-3.446) [-3.461]			-0.043 (-4.102) [-4.155]		-0.039 (-3.292) [-3.282]
R^2	0.537	0.693	0.541	0.544	0.682	0.539	0.455	0.680	0.544	0.432	0.539

Table 9**REIT Factors and Consumer Confidence Index**

This table shows the regression result on a sentiment dummy variable. The dependent variables are REIT factors constructed by size, book-to-market, momentum, asset growth, return on equity and earning surprise. The independent variable is a sentiment dummy which equals to 1 when the quarterly sentiment measure (CCI) is in the lowest quartile.

	SIZE	BM	MOM	AG	ROE	SUE
CON	0.002 (0.264)	0.014 (1.665)	-0.002 (-0.204)	0.012 (2.188)	0.005 (0.632)	0.017 (2.968)
DUMMY	0.003 (0.175)	-0.032 (-1.815)	0.093 (3.926)	-0.022 (-1.658)	0.083 (4.213)	0.053 (3.556)
R^2	-0.008	0.021	0.120	0.021	0.144	0.119

Table 10
Cross-Sectional Regressions in Subsamples

This table shows the multivariate cross-sectional regression result over two subperiods. The dependent variables are 30 REIT quintile portfolios formed by size, BM, momentum, asset growth, profitability, and earning surprise. HKM is the market equity capital ratio factor of NY Fed primary dealers by He, Kelly, and Manela (JFE, 2017). LUXCON are year-over-year log changes in luxury sales by Aït-Sahalia, Parker, and Yogo (JF, 2004). Panel A lists the cross sectional results from 1987 to 2007 (pre-crisis). Panel B list the cross-sectional result from 1994 to 2016 (reflecting the “modern” REIT era after regulatory changes in 1993).

	Panel A 1987Q1 to 2007Q4					Panel B 1994Q1 to 2016Q4				
	1	2	3	4	5	6	7	8	9	10
Constant	0.042 (4.382) [3.672]	0.017 (1.977) [1.429]	0.018 (2.314) [2.044]	0.022 (3.120) [2.270]	0.015 (1.748) [1.723]	0.039 (4.118) [3.998]	0.032 (2.665) [2.445]	0.041 (4.844) [4.710]	0.055 (5.220) [3.919]	0.043 (4.401) [4.262]
HKM	-0.071 (-2.441) [-2.099]			-0.038 (-1.569) [-1.213]	0.002 (1.376) [1.398]	-0.031 (-1.318) [-1.301]			-0.044 (-1.539) [-1.214]	-0.024 (-0.977) [-0.978]
LUXCON		-0.094 (-3.302) [-2.472]		-0.091 (-3.335) [-2.518]			-0.057 (-1.223) [-1.130]		-0.111 (-2.390) [-1.828]	
LUXCON4			-0.029 (-3.060) [-2.094]		-0.009 (-1.977) [-2.132]			-0.031 (-1.964) [-1.945]		-0.033 (-2.709) [-2.731]
R^2	0.215	0.661	0.545	0.668	0.637	0.272	0.077	0.325	0.408	0.299

Appendix

REITs Sample

We use the CRSP/Ziman Real Estate Data Series. CRSP/Ziman database include all REITs that traded on the three primary exchanges since 1980. We use equity REITs for our test (RTYPE=2). The number of firms record in CRSP/Ziman databased ranged from 55 to 199 each year. We also compare our sample to the sample identified by the National Association of Real Investment Trusts (NAREIT). The companies identified by both database are very similar.

REITs Portfolio Construction

At the beginning of each month. We sort equity REITs into five portfolios based on the following characteristic. Then we aggregate the portfolio monthly return to get portfolio quarterly return. Data used to construct portfolios can be download from CRSP and COMPUSTAT. Market Equity (Size) is the share price times the number of shares outstanding. The market equity is calculated at the beginning of each month.

Book-to Market (B/M) is the book equity divided by market equity. The B/M is calculated at June each year. The book equity is from the end of last fiscal year. The market equity is from the end of last Calendar year.

Momentum (MOM) is measured as the cumulative return in the past $t-12$ to $t-2$ month.

Investment (I/A) is the annual growth rate in total non-cash asset. Annual investment growth rate is considered know four months after fiscal year end.

Profitability (ROE) is measured as quarterly return on equity, defined as income before extraordinary item dividend by one-quarter-lagged book equity. quarterly ROE is considered known on the earnings announcement date(RDQ).

Earnings Surprise (SUE) is measured as the standardized unexpected earnings. SUE is calculated as the change in the most recent quarterly earnings per share (EPSPXQ) from its value in the same quarter last year. Divided by the standard deviation of this change over the previous eight quarters. Earnings surprise is considered known on the earnings announcement date(RDQ).

Marco Factor

TED is the spread between 3-month Libor and Treasury bill. DUNEM is year-over-year log change in aggregate unemployment rate. TERM is the spread between Treasury bonds and Treasury bills. DEF is the spread between Baa-rated and Aaa-rated corporate bonds. DIV is the aggregate quarterly dividend divided by aggregate market cap. Dividend data are from CRSP event dataset. CRSP event database document dividend per share ordered by ex-dividend day (DIVAMT). we select all ordinary dividend (DISTCD first digit=1) excluding year-end, extra dividend (DISTCD=1262) and special dividend (DISTCD=1272). The dividend ratio is calculated by using the sum of dollar amount dividend (dividend per share multiply number of share outstanding) within each quarter divided by the total market capitalization at the end of each quarter.

Market Factor

MKT is the value weighted excess return of SP500 stocks. REIT_MKT is the value weighted excess return of all equity REITs identified by CRSP/Ziman database. LTR is the long-term bond excess return. CORPR is the corporate bond excess return.

Limited Stock Market Participation Factors

A. Stockholder consumption growth

Following Malloy, Moskowitz, and Vissing-Jorgensen (2009), we use the Consumer Expenditure Survey (CE) data to construct stockholder consumption growth factor. CE interviewed 4000~8000 household each quarter. Each household is interviewed once every three months over four consecutive quarters. About 20% sample households are replaced for each interview. The first interview is a practice interview and the results are not report in the data. The interview data only includes result from interview two to five.

The sample period is from 1982 to 2016. Sample from 1996 to 2016 can be directly download from Public-Use Microdata (PUMD) from CE website. The early sample 1982 to 1995 can be download from ICPSR website.

First, we classify all types of expenditure into durable, nondurable and service by NIPA definition. All durable items are excluded. As for the service, we exclude all housing expense (but include house operation cost), medical and education cost; we exclude the rental and finance expense for durable product (such as car finance). We also exclude all miscellaneous items since it is too ambiguous to classify. Table A1 shows the UCC (six-digit codes that identify the consumption item) we use for calculating household consumption.

Second, we construct household consumption growth. In each quarter, interviews are spread out in each month. This means that there are households get interviewed in each month. Thus, we can calculate the quarterly growth rate at a monthly frequency. For example, if a household got its third interviewed in May, it reported its consumption in February, March, April. This household would get its fourth interview in August and it would report its consumption in May, June, July. This household's consumption growth in July is calculated as follows:
$$\log(\text{total consumption reported in fourth interview}) - \log(\text{total consumption reported in third interview}).$$

Then we merge the household consumption growth data to household characteristics data. We clean the data with the following criteria: Any household with less than four interviews will be dropped. Nonurban households (variable: BLS_URBN) and households residing in student housing (variable: CUTENURE) are dropped. Households with incomplete income response (variable: REPSTAT) will be dropped. we also drop the observations for which the consumption growth ratio is less than 0.2 or greater than 5.

Last, we identify the stockholder in our sample and calculate the stockholder consumption growth rate. In the fifth interview, households will be asked the amount of stock, bonds, mutual fund they hold today and the amount they hold one year from today. The interview on financial information is a snapshot for the stockholding, a household might report zero holding if it sold all the stock right before the interview. In order to include all potential stockholders, we classify households with either positive holding today or positive holding one year ago today as stockholder. Then, we will take average of all stock holder consumption growth rate within each month to get the stockholder consumption growth factor.

B. Luxury consumption

Referring to Sahalia, Parker, and Yogo (2005). We use the sales of the high-end luxury goods to construct consumption growth factor. The high-end luxury good should not be considered as durable goods for the very rich since fashion is fickle.

The luxury retailer we use are Cucci (GUC), Saks (SKS) and Tiffany (TIFF, TIF since 1986). Their quarterly sale data can be get from COMPUSTAT. The sample period for Cucci and Saks are short. Cucci's sale data is available from 1995 to 2004. Saks's sale data is available from 1991 to 1997. Tiffany has the longest sample period which is from 1960 until now.

COMPUSTAT reports the quarterly sale (turnover) data for all public companies. COMPUSTAT segment reports the annual US sale and annual international sale data for all public companies. Using COMPUSTAT segment data, we can calculate the ratio of US retail to the total sale each year. Then, we multiply this ratio by the quarterly total sale to get quarterly US sale. The luxury good consumption growth is deseasonalized by computing growth rate with respect to the same quarter in the last year.

C. Intermediary Capital Ratio

He, Kelly, and Manela (2017) creates the intermediary capital ratio, which is the aggregate capital ratio of the New York Fed's Primary dealer. The intermediary capital ratio is denoted as aggregate value of market equity divided by aggregate market equity plus aggregate book debt. Their factor could download at <http://www.zhiguohe.com/research.html>

D. Intermediary Leverage Ratio

Adrian, Etula, and Muri (2014) constructs intermediary leverage ratio, which is the total financial asset divided by the difference of total financial assets and total liability. The broker-dealer leverage index data can be download from Financial Accounts of the United states in Federal Reserve Website <https://www.federalreserve.gov/releases/z1/current/default.htm>.

E. Capital Share

Lettau, Ludvigson, and Ma (2018) constructs capital share. The relation between labor share and capital share is $KS=1-LS$. They calculate the labor share growth rate by taking the log difference of quarterly seasonally adjusted labor share index. The capital share growth rate is the labor share growth rate with opposite sign. The labor share index can be found at <http://research.stlouisfed.org/fred2/series/PRS85006173>.

The macro variable includes DUNEM (year-over-year log change in aggregate unemployment rate). TERM (the spread between Treasury bonds and Treasury bills). DEF (the spread between Baa-rated and Aaa-rated corporate bonds) and dividend ratio. The market variables are excess stock market return, excess equity REITs market return, excess long-term bond return, and excess corporate bond return. See Appendix for more detail.

Table A1. List of UCC

Referring to NIPA, we include UCC which represent nondurable goods and service. We exclude durable goods and some service with substantial durable components.

Category	UCC
FOOD	190904, 790220, 790230 190901, 190902, 190903, 790410, 790430, 800700
ALCOHOL	200900, 790310, 790320, 790420
HOUSEHOLD OPERATION	340310, 340410, 340420, 340520, 340530, 340903, 340906, 340910, 340914, 340915, 340211, 340212, 670310, 330511, 340510, 340620, 340630, 340901, 340907, 340908, 690113, 690114, 990900
UTILITY	260211, 260212, 260213, 260214, 260111, 260112, 260113, 260114, 250111, 250112, 250113, 250114, 250211, 250212, 250213, 250214, 250221, 250222, 250223, 250224, 250901, 250902, 250903, 250904, 270102, 270130, 270104, 270101 270211, 270212, 270213, 270214, 270411, 270412, 270413, 270414, 270901, 270902, 270903, 270904
APPAREL	360110, 360120, 360210, 360311, 360312, 360320, 360330, 360340, 360350, 360410, 360511, 360512, 360901, 360902, 370110, 370120, 370130, 370211, 370212, 370213, 370220, 370311, 370312, 370313, 370902, 370903, 370904, 380110, 380210, 380311, 380312, 380313, 380320, 380331, 380332, 380340, 380410, 380420, 380430, 380510, 380901, 380902, 380903, 390110, 390120, 390210, 390221, 390222, 390230, 390310, 390321, 390322, 390901, 390902, 410110, 410120, 410130, 410140, 410901, 400110, 400210, 400220, 400310, 420110, 420120, 430110, 430120, 440110, 440120, 440130, 440140, 440150, 440210, 440900
PERSOANL CARE	640130, 640420, 650310
READING	590111, 590112, 590211, 590212
TOBACCO	630110, 630210
MEDICAL	540000
ENTERTAINMENT	610900, 620111, 620121, 620122, 620211, 620212, 620221, 620222, 620310, 620903, 270310, 340610, 340902, 340905, 620904, 620912
INSURANCE/ CASH CONTRIBUTION	002120, 700110, 800910, 800920, 800931, 800932, 800940
TRANSPORTATION	470111, 470112, 470113, 470211, 470212, 530110, 530210, 530312, 530411, 530510, 530901, 530311, 530412, 530902

Essay 2:

Mispricing in REITs Market

Abstract

This paper focuses on the relationship between REIT stock prices and REIT net asset values (NAV). By investigating two prevailing sets of NAV data from Green Street Advisors and S&P Global Market Intelligence (formerly the SNL Financial dataset), we find that REIT stock prices deviate substantially from their NAV. A long-short strategy based on the premium to NAV yields about 1% return per month. Due to the high institutional ownership in REIT markets, we then exam whether institutional investors are rational and whether they trade against mispricing. The evidence contradicts the sophisticated institutional investor hypothesis. We find that institutional investors tend to buy overvalued REITs and sell undervalued REITs. Furthermore, our results may shed light on popular asset pricing anomalies. By checking the premium to NAV of REIT anomaly portfolios, we conclude that the ranking of momentum and earnings surprise could be used as a proxy for mispricing in REIT markets.

1. Introduction

Testing mispricing in the stock market remains contentious because of the difficulty in measuring the intrinsic value of equities. Early literature uses the book to market ratio as proxy measure for mispricing. Hirshleifer and Jiang (2010) use equity and debt financing to identify common misvaluation across firms. Stambaugh and Yuan (2016) use the ranking of the anomalies to measure the level of mispricing. All of these measurements are proxies for mispricing, there are few direct measures for the intrinsic value of a stock.

In this paper, we focus on the market for real estate investment trusts (REITs). A REIT is a company whose assets mainly consist of commercial or residential properties. If there is no arbitrage, the underlying asset value should be equal to the market value of the REIT. It is easier to estimate the intrinsic value for REIT stocks as opposed to common stocks as the net asset value of real estate properties can be valued fairly accurately by real estate professionals (appraisers). We obtain net asset value data from Green Street Advisors and S&P Global Market Intelligence (formerly the SNL Financial dataset). Comparing the net asset value of a REIT to its market value gives us a direct measurement for mispricing.

We find that REIT stock prices deviate substantially from their NAV and REIT returns are negatively correlated with the premium to net asset value ratio. Overvalued REITs (price greater than NAV) yield higher returns than undervalued REITs. The long-short strategy based on net asset values could yields around 1% return monthly.

Our study could also shed light on the debate about the rationality of institutional investors. Since the 1980s, retail investors are assumed to be the source of mispricing. DeLong (1990) argue that noise traders can drive price significantly away from fundamental values. Da, Engelberg and Gao (2015) have shown that there is a growing consensus that noise traders can induce large price

movements. On the other hand, institutional investors are considered to be sophisticated and rational. Institutional investors are the arbitragers who will trade against mispricing. Stanbough (2014) finds that active management corrects most noise trader induced mispricing and the mispricing is reduced when the percentage ownership of institutional investors increase. Contrary to this well-established view, recent empirical work from Edelen, Ince and Kadlec (2016) find that institutional investors do not always appear to behave rationally, in that they buy overvalued stocks and short undervalued stocks. Furthermore, Devalut, Sias and Starks (2019) find that sentiment, which is a factor widely used to explain mispricing, captures institutional rather than retail investors' demand. The REIT market is an ideal laboratory for testing institutional investor behavior since investing in commercial real estate requires sophisticated knowledge and around 80% of the investment in REIT markets are undertaken by institutional investors. To investigate this issue, we sort REIT stocks by their premium to NAV and track the change in institutional ownership for each portfolio. Our results reject the sophisticated institutions hypothesis. We find that institutional investors prefer overvalued REITs to undervalued REITs. The evidence from 13f institutional holding data indicates that the number of institutional investor is larger for overvalued REITs than undervalued REITs.

This paper also gives some insight into our understanding of the popular asset pricing anomalies. Stambaugh and Yuan (2015) use a ranking of the anomalies to measure the level of mispricing. Taking momentum as an example, they assume stocks with high momentum ranking (the past winner stocks) are more likely to be the overvalued and stocks with low momentum ranking (the past loser stocks) are more likely to be undervalued. Their mispricing measure is constructed by the ranking of 11 anomalies. We test their hypothesis by checking the premium to NAV for each anomaly portfolio. We find that returns on equity, earning surprise and momentum

ranking are positively related to mispricing, while the ranking for investment to asset is negatively related to mispricing.

The rest of the paper is organized as follows. We review the literature in Section 2. Section 3 describes the data and methodology used. Section 4 reports the empirical results and Section 5 provides a summary and concludes.

2. Literature Review

A widely accepted axiom of financial theory states that the fundamental value of a security should equal the present value of its future cash flows. Kaplan and Ruback (1995) suggests that discounted cash flow valuation methods provides the most reliable estimate of market value. However, assets appear to be mispriced at some times. In order to verify mispricing, one practical problem is how to measure the intrinsic value of securities. Abarbanell and Bernard (1995) assume that US stock markets overvalue short term earning and undervalue long-term earnings. They use an accounting-based valuation model to estimate mispricing. Frankel and Lee (1997, 1998) estimate a firm's fundamental value (V) by consensus forecasts and a residual income model. They find that the V/P ratio is a good predictor of long-term cross-sectional returns. Hirshleifer and Jiang (2010) assume that firms issue equity in response to overpricing and repurchase in response to underpricing. They use external financing activities to identify mispriced stocks and construct a mispricing factor (UMO). They find that the loading on the UMO factor can predict cross-sectional stock returns. Stambaugh and Yuan (2016) use a ranking of the anomalies to measure the relative mispricing level.

When it comes to the study of mispricing in REIT markets, most research focuses on investment sentiment. Early work by Clayton and McKinnon (2003), and Gentry, Jones and Mayer

(2004) extended the literature on sentiment in closed-end fund discounts to REIT pricing relative to net asset value. Lin, Rahman, Yung (2008) show that investor sentiment is positively related to REITs return. Ling, Naranjo and Scheik (2014) find a positive relationship between measures of investor sentiment for private real estate markets and subsequent period real estate returns. However, long-horizon regressions show this sentiment is associated with possible mispricing. Das et al. (2015) show that the sentiment of institutional investors “spills over” from private real estate markets to public markets and highlights the role of economic conditions in determining the direction of this spillover.

3. Data

The sample used in this paper consists of all equity REITs listed in the CRSP/Ziman database from 1993 to 2016. During the sample period, the market capitalization of all equity REITs grew from 12 billion dollars to one trillion dollars and the number of REITs each year grew from 108 to 188. Data on REIT returns are from CRSP and the accounting data are from COMPUSTAT. We follow Fama and French (1992) to construct the REIT based size, book to market and momentum portfolios. We follow Following Hou, Xue, and Zhang (2015) and Bond and Xue (2017) to construct REIT-based investment, profitability and earning surprise portfolios.

The net asset value (NAV) used in this paper is obtained from Green Street Advisors and S&P Global Market Intelligence. S&P provided us with historical monthly consensus NAV data from 2001 to 2017. Green Street Advisors provided their historical NAV data from 1989 to 2017. However, Green Street only reported quarterly NAV data before 1994 and reported monthly NAV after 1994. So, we use data on Green Street NAVs from 1994 to 2016 in this paper. Our mispricing

variable is the premium to NAV, which is calculated by using the REIT stock price on the NAV release day divided by the NAV less one. That is:

$$\text{premium to NAV} = \frac{\text{stock price on the NAV release day}}{\text{NAV}} - 1$$

The NAV release date for S&P Global is the first day of each month. Green Street provided us with all the release dates (RESM date) from their monthly NAV report. The RESM date is around the first trading day of each month.

Table 1 provides summary statistics for the premium to net asset value from Green Street Advisors. The Green Street covers about 40% of the number of equity REITs each year. Their sample consists primarily of large REITs and their market capitalization reflects around 72% of the market total capitalization of all equity REITs. Table 2 compares the firm characteristics of all equity REITs to the subsample of REITs covered by Green Street Advisors. We can clearly see that Green Street covers largest REITs, as the average market capitalization of their sample is twice as much as the market capitalization of all equity REITs; The 25th percentile market capitalization of the Green Street sample is even larger than the median size of all equity REITs. The size difference between the two samples also reflects the difference in institutional holding. The average number of institutional holders for the Green Street sample is 154 and the average number of institutional holder for all equity REITs is 80.7. Table 2 also shows that firms covered by Green street tend to be growth firms. Their book to market value is about 0.55, while the book to market ratio of all equity REITs is about 0.88. As for REIT characteristics such as return on equity (ROE), earning surprises (SUE) and investment to assets (I2A), the distribution of both samples are very similar.

Figure 1 plots the time series of the average premium to NAV. The time series constructed using Green Street data is highly correlated with the time series constructed using the S&P consensus data - 82%. The aggregate premium is stationary and mean reverting. We regress REIT market returns and SP500 returns on the lagged aggregate premium to net asset value. However, we find that the aggregate premium to NAV has no forecasting power for market returns.

Institutional ownership data is obtained from the Thomson Financial 13f database over the period January 1980 to December 2015. Follow Edelen, Ince and Kadlec (2016), institutional demand is measured as the change in the number of institutions ($\Delta\#instit$),

$$\Delta\#instit_{i,t} = \frac{\# \text{ of inst. holding stock } i \text{ at quarter } t - \# \text{ of inst. holding stock } i \text{ at quarter } t - 1}{\# \text{ of inst. holding stock } i \text{ at quarter } t - 1}$$

Table 7 provides the summary statistics for institutional ownership in the REIT market. On average, the number of institutional investors is increased by 20% per year and the percent of shares hold by institutional investors is increased by 1% per year.

4. Methodology and Results

4.1 Cross-sectional REITs Return and Premium to NAV

Table 3 reports the aggregate daily return for portfolios sorted on the premium to NAV. Green Street reported NAV for 43 equity REITs in 1993, and this number increased to 83 in 2016. In each month, we construct REIT portfolios at the reporting day ($K=0$). The average premium to net asset value for quintile 1 is -0.171 and the average premium to net asset value for quintile 5 is 0.256. We then exam aggregate value-weighted portfolio returns from the next trading day and covering up to the following 80 trading days. In the first day after the reporting date, low premium to NAV REIT stocks yield higher return than high premium to NAV REITs stocks. The return

difference between quintile 1 and quintile 5 REITs is 0.17% which is statistically significant. The return spread become larger as we extend the holding period. The cumulative return spread reaches 0.5% over the next 10 business days and reaches 1% over 20 business days. The spread stops increasing after 30 business days and the remain close to 1% after 80 trading days. We also run the cross-sectional tests over different subsample periods. In the first half of the sample the difference in the aggregate return on the two portfolios reaches 0.92% after 30 business days following the report date. In the second half sample, the portfolio return shows a similar trend. Even though the return differences are not statistically significant, due to the large negative returns experienced during the 2008 financial crisis, they are still economically significant.

We run the same test using NAV data from S&P Global. S&P report NAV data on the first day of each month from 2001 to 2016. To ensure the NAV information is in investors' information set, we construct premium to NAV portfolios on the first trading day of each month. The results using S&P data is similar to that obtained with the Green Street data. The low premium to NAV quintile yields higher returns than high premium to NAV quintile. The return difference increases and reaches a peak of 1.25% after 30 trading days following the report date. Table 4a reproduces the cross sectional results using Green Street data with the same sample period from 2001 to 2016 (in order to match the S&P sample period). The portfolio aggregate returns show a similar pattern.

Table 5 reports multivariate cross-sectional regression results. For each firm, we regress the monthly return on a set of firm characteristics, including the premium to NAV. Consistent with previous literature, we find past cumulative returns (momentum) have significant explanatory power and the regression coefficient is positive. Column 3 shows that momentum have explanatory power while size and book to market do not. We also find ROE and SUE have significant

explanatory power for the cross-sectional of REIT returns. Column 4 shows that ROE and momentum have a similar level of explanatory power. Columns 1, 3, 5, 6, 7, 8 suggest that Premium to NAV (P2nav) have significant explanatory power and their regression coefficient is negative, which means that high premium to NAV indicate low future returns. Columns 3, 5, 6 show that p2nav drives out momentum and SUE. The cross-sectional regression results are consistent with the results in table 3 and table 4. Premium to net asset value has explanatory power for the cross section of REIT returns.

4.2 Institutional Demand and Premium to NAV

REITs have high institutional ownership with the percent of institutional investor continuing to grow each year. If institutional investors are rational and trade against mispricing, we should observe less mispricing in the later sample. However, Table 3 panel C and Table 4 panel C tell a different story. The premium to NAV still has strong predicting power for cross-sectional REIT returns in the second half of the sample. The return difference between overvalued REITs and undervalued REITs is actually greater in the later part of the sample than that in early sample. One natural question that arises is: Do institutional investors correct mispricing? Table 8 documents changes in institutional holdings during the portfolio formation period. We follow Edelen, Ince and Kadlec (2016) to construct portfolios and calculate institutional holding changes. We construct tertile portfolios based on premium to NAV and other firm characteristics. UMO shows the six quarter institutional holding change for portfolios sorted by the premium to NAV. It can be seen that a significantly greater number of institutional investors buy overvalued stocks than undervalued stocks. UMO1 shows the one quarter institutional holding change for portfolios

sorted by premium to NAV. $\Delta\#Inst$ for overvalued stock is 3.3% and $\Delta\#Inst$ for undervalued stock is 1.45%. We also sort the UMO portfolio using the average premium to NAV over the past three month. The results still suggest that institutional investors tend to buy overvalued REITs. UMO_shock sorts portfolios based on the institutional holding change over the past month. The results indicate that if a REIT stock become more overvalued than last month, more institutional investors will hold that stock.

Are institutional investors noise traders? The results in Table 3 suggests that institutional investor could be the noise traders who drive REIT prices away from their fundamental value. We further explore this question via following the approach of DeVault, Sias and Starks (2019). That is, we exam the time series relationship between institutional demand shocks and investor sentiment. Baker and Wurgler (2006) propose that sentiment traders shift from safe to speculative stocks when sentiment increases and these sentiment-induced demand shocks drive mispricing. In Table 9, all equity REITs are sorted into five portfolios based on their idiosyncratic volatility. We then calculate institutional demand shocks by averaging the cross-sectional change in institutional holdings within each ivol portfolio. Columns 2 and 3 present the correlation between institutional investor demand shocks and sentiment. We find that high ivol stocks (speculative stocks) tend to have higher correlation with sentiment than low ivol stocks (safe stocks). The results indicate that sentiment appears to better capture the demand of institutional investors rather than that of individual investors.

Focusing on the anomaly sorted portfolios, we find that institutional investors follow momentum, earning surprise (SUE) and return on equity (ROE). $\Delta\#Inst$ is larger for the long leg of these three anomalies. $\Delta\%Inst$ difference between the long short legs is significant for

momentum and SUE. However, institutional investors trade against investment to asset (I2A) anomalies. They tend to invest more in aggressive stocks than conservative stocks. We also find that $\Delta\#Inst$ is larger for small size stocks than for large size stocks but $\Delta\%Inst$ shows the opposite result. This result might be due to the equal weighted average giving more weight to small size firms as the $\Delta\#Inst$ is usually large for small firms.

4.3 REIT Anomalies and Premium to Net Asset Value

Stambaugh and Yuan (2016) use a ranking of the anomalies to measure the level of mispricing. They assume stocks with higher anomaly rankings tend to be overvalued stocks and stocks with lower anomaly rankings tend to be undervalued stocks. We test this hypothesis the using the premium to NAV as a benchmark measure for mispricing. Table 6 shows the premium to NAV for each anomaly portfolio. At the beginning of each month, we sort all equity REITs into quintile portfolios based on their size, book to market, past returns, earning surprises, investment to assets and return on equity (see appendix for more detail). Column 2 presents the value weight portfolio return minus the risk free rate. Consistent with previous literature, REITs have weak size effect and no value effect. The return of small size REIT stocks is greater than the return of large size stocks but the dispersion is only 0.14% per month and statistically insignificant. Since not all REITs have premium to net asset value information available, we calculate the value weighted premium to NAV and equal weighted premium to NAV within each portfolio. The average premium to net asset value is positive for large size stocks which means large size stocks tend to be overvalued. This finding is consistent with Clayton and Mackinnon (2000). The long leg of momentum, SUE and ROE has a larger premium to net asset value than their corresponding short

leg. The premium to net asset value differences are economically and statistically significant. However, the long leg of Investment to assets has lower premium to net asset value than its short leg. This results suggest that the ranking of momentum and ROE could be used as a proxy for mispricing in REIT markets; Ranking of SUE could represent the relative mispricing level since the stocks with low SUE still have positive premium to NAV on average. The ranking of investment to assets is not a proper a proxy for mispricing.

5. Conclusion

In this paper, we study the Net Asset Value and its implication for REIT pricing. First, we find that REIT prices can deviate substantially from their net asset values. The long short strategy based on the premium to net asset value yields and average return of 1% each month. The premium to NAV has significant explanatory power for the cross-section REIT returns.

Second, we test the relation between the premium to NAV and widely documented anomalies. The results indicate that REITs with high momentum, high ROE and high SUE tend to be overvalued and REITs with high investment to assets tend to be undervalued. The hypothesis that rankings of the anomalies could proxy for mispricing level may not hold for all anomalies.

Last, we explore the implications of changes in institutional investor demand in the REIT markets. We find that institutional investors more likely to be the noise traders in the market and they do not appear to trade against mispricing. Instead, they tend to hold more overvalued REIT stocks rather than undervalued REIT stocks. Our evidence also suggests that institutional investor demand shocks are correlated with investor sentiment.

Figure 1. Premium to Net Asset Value, 2001-2017. Figure 1 displays the monthly series of the market-wide premium to net asset value. The solid line is the market-wide premium to net asset constructed from SNL Financial. The Dashed Line is the market-wide premium to net asset value constructed from Green Street Advisor

Figure 2. Cumulative Daily Returns of the Overvalued Portfolio (Solid Line) and Undervalued Portfolio (Dashed line), 2001 to 2016. Figure 2 displays the cumulative daily returns of the lowest premium to net asset value portfolio (quintile 1) and the highest premium to net asset portfolio (quintile 5).

Table 1. Summary Statistic for Premium to NAV

This table reports summary statistics of premium to NAV from Green Street Advisor. N is the number of REITs covered by Green Street Advisor each year. #GS/all is the number of equity REITs covered by Green Street divided by the total number of Equity REITs in United States. M GS/all is the total market cap of Green Street REITs divide the total market cap of all equity REITs in United States.

year	N	P20	P40	P50	P60	P80	#Gs/all	M GS/all
1989	25	-0.1909	-0.1334	-0.1000	-0.0703	-0.0189	29.4%	74.2%
1990	27	-0.4079	-0.3168	-0.2601	-0.2222	-0.1096	31.0%	88.3%
1991	28	-0.3478	-0.2247	-0.1870	-0.1500	0.0685	25.7%	69.4%
1992	29	-0.2850	-0.1852	-0.0961	-0.0424	0.1718	26.1%	68.5%
1993	43	-0.1077	0.0230	0.0848	0.1354	0.3318	27.6%	51.8%
1994	58	-0.1228	-0.0326	0.0217	0.0575	0.1719	28.6%	50.2%
1995	63	-0.0968	-0.0241	0.0063	0.0330	0.1316	30.6%	54.5%
1996	66	0.0159	0.0811	0.1133	0.1508	0.2527	32.0%	53.4%
1997	70	0.1292	0.1939	0.2371	0.2743	0.3681	32.7%	51.9%
1998	72	-0.0573	0.0133	0.0439	0.0769	0.1778	34.1%	70.3%
1999	70	-0.1827	-0.1221	-0.0956	-0.0699	0.0035	35.2%	68.6%
2000	68	-0.2128	-0.1539	-0.1262	-0.0991	-0.0269	36.6%	72.6%
2001	67	-0.0963	-0.0465	-0.0253	-0.0043	0.0534	38.1%	73.5%
2002	66	-0.0629	-0.0024	0.0262	0.0581	0.1398	39.3%	74.0%
2003	64	-0.0166	0.0542	0.0923	0.1225	0.2317	38.3%	72.1%
2004	65	0.0048	0.0746	0.1050	0.1368	0.2402	37.4%	66.9%
2005	69	-0.0742	-0.0102	0.0234	0.0540	0.1272	40.6%	74.6%
2006	72	-0.0840	-0.0213	0.0132	0.0442	0.1286	43.4%	80.4%
2007	69	-0.2382	-0.1446	-0.1047	-0.0610	0.0450	47.9%	88.5%
2008	62	-0.3614	-0.2332	-0.1783	-0.1196	0.0162	51.2%	70.5%
2009	64	-0.3013	-0.0396	0.0500	0.1337	0.2876	53.3%	79.0%
2010	76	0.0145	0.0995	0.1350	0.1744	0.2765	59.8%	82.2%
2011	82	-0.1117	-0.0073	0.0487	0.0859	0.1781	61.7%	86.4%
2012	80	-0.0764	0.0259	0.0650	0.1039	0.2173	55.6%	84.8%
2013	83	-0.0967	-0.0215	0.0106	0.0569	0.1992	51.2%	80.4%
2014	86	-0.0824	-0.0239	0.0130	0.0409	0.1265	49.7%	79.0%
2015	89	-0.1656	-0.0864	-0.0472	-0.0099	0.0937	47.3%	78.2%
2016	83	-0.1734	-0.0923	-0.0387	0.0200	0.1540	44.1%	71.7%
2017	79	-0.1644	-0.0671	-0.0254	0.0155	0.1270	42.2%	69.6%
Mean	64.7	-0.1363	-0.0491	-0.0067	0.0319	0.1436	40.4%	71.9%

Table 2. Distributional Statistics for REITS Characteristics

This table presents the time-series average of the cross-sectional mean, standard deviation, and percentile for REITs characters from 1993 to 2015. The REITs characters include market equity (SIZE) in millions, book to market equity (BM), past 2 to 12 months aggregate return (RET2_12), return on equity (ROE), share turnover (TN), investment to asset (I2A), standardized unexpected earning (SUE), number of institutional investors (NII).

	Panel A: All Equity REITs (n=148)					Panel B: REITs covered by Green Street Advisor (n=60)				
	MEAN	SD	P25	P50	P75	MEAN	SD	P25	P50	P75
SIZE	1571.99	3678.54	92.68	455.67	1561.38	3295.35	5280.67	849.87	1739.34	3392.42
BM	0.876	1.233	0.435	0.638	0.934	0.555	0.297	0.364	0.497	0.669
RET2_12	0.152	0.482	-0.026	0.122	0.276	0.140	0.287	0.236	0.134	0.274
TN(%)	0.427	0.515	0.117	0.276	0.541	0.679	0.631	0.294	0.491	0.853
ROE	0.018	0.128	0.007	0.018	0.028	0.021	0.073	0.008	0.017	0.027
SUE	0.157	1.727	-0.442	0.027	0.609	0.267	1.81	-0.421	0.090	0.699
I2A	0.164	0.440	-0.016	0.062	0.214	0.171	0.333	0.005	0.069	0.203
NII	80.7	93.2	38.2	70.2	103.5	153.8	94.6	103.2	131.3	172.6

Table 3. REITs Aggregate Daily Returns for Portfolios Formed Using Sorts on Premium to NAV from Green Street Advisor

This table displays the aggregate daily return of portfolios sorted by premium to net asset value. These portfolios are held for K days. K=0 is the releasing day. Returns are in percentage; the t-statistics are reported in parentheses. The mean premium to net asset value are reported in bracket in the first column.

Panel A: Sample from 1993-2016

	K=0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	0.03	0.33	0.36	0.68	0.71	1.12	1.34	2.12	2.10	2.58	3.36	4.71
[-0.171]	(0.23)	(2.30)	(1.97)	(1.84)	(1.73)	(2.04)	(2.34)	(3.08)	(2.69)	(3.38)	(3.77)	(4.69)
P2	0.01	0.19	0.12	0.28	0.23	0.71	0.85	1.49	1.27	1.91	2.47	3.68
[-0.059]	0.08	(1.53)	(0.68)	(0.87)	(0.64)	(1.52)	(1.72)	(2.64)	(2.18)	(2.93)	(3.55)	(4.71)
P3	0.05	0.21	0.20	0.23	0.24	0.63	0.81	1.34	1.17	1.74	2.50	3.52
[0.010]	(0.43)	(1.90)	(1.3)	(0.85)	(0.80)	(1.61)	(1.93)	(2.81)	(2.46)	(3.20)	(4.04)	(5.06)
P4	0.10	0.17	0.04	0.13	0.01	0.41	0.68	1.24	1.03	1.68	2.36	3.50
[0.089]	(0.87)	(1.58)	(0.29)	(0.52)	(0.04)	(1.17)	(1.86)	(3.01)	(2.43)	(3.64)	(4.44)	(5.68)
Overvalued	0.15	0.16	0.07	0.17	0.12	0.47	0.69	1.05	0.97	1.64	2.42	3.73
[0.256]	(1.34)	(1.63)	(0.52)	(0.72)	(0.48)	(1.44)	(1.95)	(2.69)	(2.40)	(3.64)	(4.47)	(6.29)
UMO	-0.12	0.17	0.29	0.52	0.59	0.66	0.65	1.07	1.13	0.94	0.93	0.98
[0.427]	(-2.13)	(2.43)	(3.44)	(2.70)	(2.37)	(1.91)	(1.87)	(2.38)	(2.39)	(1.92)	(1.70)	(1.52)

Panel B: Sample from 1993-2004

	K= 0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	0.20 (2.35)	0.21 (2.79)	0.28 (2.53)	0.57 (2.86)	0.75 (2.91)	1.09 (3.39)	1.39 (3.89)	1.85 (4.52)	1.94 (4.25)	2.43 (4.93)	3.16 (5.26)	4.48 (6.46)
P2	0.18 (2.33)	0.12 (1.76)	0.16 (1.48)	0.28 (1.64)	0.31 (1.26)	0.73 (2.36)	0.90 (2.77)	1.49 (3.93)	1.47 (3.93)	2.08 (4.51)	2.83 (4.87)	4.08 (6.21)
P3	0.25 (3.07)	0.13 (1.81)	0.14 (1.35)	0.19 (1.11)	0.22 (0.87)	0.51 (1.63)	0.69 (2.00)	1.21 (3.30)	1.27 (3.30)	1.66 (3.67)	2.39 (4.44)	3.60 (5.63)
P4	0.30 (3.88)	0.12 (1.86)	0.04 (0.37)	0.13 (0.71)	0.01 (0.05)	0.30 (0.92)	0.66 (1.84)	1.32 (3.22)	1.21 (3.22)	1.82 (3.74)	2.46 (4.34)	3.69 (5.63)
Overvalued	0.31 (3.87)	0.10 (1.58)	0.06 (0.56)	0.16 (0.89)	0.14 (0.59)	0.37 (1.25)	0.59 (1.75)	1.00 (2.68)	1.02 (2.41)	1.66 (3.77)	2.42 (4.35)	3.79 (6.02)
UMO	-0.11 (-1.96)	0.10 (1.90)	0.22 (2.87)	0.41 (3.13)	0.60 (3.46)	0.72 (3.40)	0.80 (3.60)	0.85 (3.19)	0.92 (3.25)	0.77 (2.45)	0.74 (1.89)	0.69 (1.46)

Panel C: Sample from 2005-2016

	K=0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	-0.13 (-0.52)	0.44 (1.67)	0.55 (1.52)	0.87 (1.06)	0.69 (0.93)	1.18 (1.17)	1.30 (1.25)	2.37 (1.84)	2.26 (1.72)	2.73 (1.93)	3.53 (2.20)	4.94 (2.67)
P2	-0.15 (-0.68)	0.23 (1.02)	0.16 (0.47)	0.25 (0.35)	0.23 (0.35)	0.74 (0.88)	0.87 (0.98)	1.50 (1.43)	1.09 (1.03)	1.76 (1.47)	2.27 (1.82)	3.30 (2.37)
P3	-0.14 (-0.65)	0.30 (1.50)	0.33 (1.09)	0.18 (0.31)	0.28 (0.54)	0.78 (1.13)	0.96 (1.31)	1.46 (1.69)	1.07 (1.28)	1.81 (1.87)	2.51 (2.35)	3.45 (2.84)
P4	-0.09 (-0.46)	0.24 (1.25)	0.12 (0.40)	0.08 (0.16)	0.05 (0.10)	0.55 (0.92)	0.73 (1.20)	1.16 (1.65)	0.85 (1.21)	1.55 (2.01)	2.22 (2.55)	3.32 (3.22)
Overvalued	-0.01 (-0.06)	0.21 (1.22)	0.14 (0.53)	0.07 (0.16)	0.15 (0.36)	0.60 (1.09)	0.86 (1.41)	1.09 (1.62)	0.93 (1.36)	1.63 (2.10)	2.43 (2.82)	3.67 (3.70)
UMO	-0.12 (-1.29)	0.23 (1.83)	0.41 (2.62)	0.79 (1.92)	0.54 (1.23)	0.58 (0.93)	0.44 (0.71)	1.29 (1.53)	1.33 (1.51)	1.10 (1.22)	1.10 (1.07)	1.26 (1.07)

Table 4. REITs Aggregate Daily Returns for Portfolios Formed Using Sorts on Premium to NAV from SNL Consensus

This table displays the aggregate daily return of portfolios sorted by premium to net asset value. These portfolios are hold for K days. K=0 is the releasing day return. Returns are in percentage; the t-statistics are reported in parentheses. The mean premium to net asset value are reported in bracket in the first column.

Panel A: Sample from 2001 to 2016

	K=0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	0.06 (0.30)	0.26 (1.61)	0.31 (1.42)	0.58 (1.25)	0.55 (1.02)	1.04 (1.48)	1.44 (1.93)	2.37 (2.53)	2.26 (2.44)	2.87 (2.93)	3.86 (2.94)	3.45 (2.01)
P2	0.01 (0.04)	0.20 (1.39)	0.21 (1.01)	0.25 (0.62)	0.27 (0.62)	0.78 (1.24)	1.18 (1.76)	1.90 (2.40)	1.64 (2.03)	2.30 (2.84)	2.91 (2.37)	3.23 (1.97)
P3	-0.04 (-0.25)	0.18 (1.28)	0.13 (0.62)	0.06 (0.17)	-0.09 (-0.23)	0.33 (0.63)	0.75 (1.36)	1.46 (2.36)	1.15 (1.86)	1.75 (2.49)	2.44 (2.62)	2.86 (2.30)
P4	0.03 (0.17)	0.15 (1.12)	0.14 (0.17)	0.12 (0.35)	-0.04 (-0.11)	0.42 (0.90)	0.80 (1.63)	1.31 (2.37)	1.00 (1.75)	1.75 (2.71)	2.64 (3.03)	3.00 (2.47)
Overvalued	-0.03 (-0.21)	0.13 (1.07)	0.05 (0.03)	0.01 (0.03)	-0.10 (-0.29)	0.39 (0.94)	0.79 (1.81)	1.21 (2.41)	1.02 (1.97)	1.93 (3.25)	2.52 (3.16)	2.91 (2.70)
UMO	0.09 (1.26)	0.13 (1.82)	0.27 (2.38)	0.59 (2.22)	0.65 (1.91)	0.66 (1.52)	0.65 (1.40)	1.16 (1.79)	1.25 (1.93)	0.94 (1.48)	1.29 (1.56)	0.43 (0.44)

Panel B Sample from 2001 to 2008

	K =0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	0.16 (0.51)	0.22 (0.97)	-0.02 (-0.09)	0.25 (0.32)	-0.25 (-0.28)	0.11 (0.10)	0.40 (0.36)	1.25 (0.97)	0.76 (0.55)	0.58 (0.41)	0.20 (0.11)	-0.37 (-0.15)
P2	0.09 (0.33)	0.09 (0.51)	-0.11 (-0.42)	-0.13 (-0.19)	-0.54 (-0.79)	-0.19 (-0.21)	0.00 (0.00)	0.78 (0.77)	-0.03 (-0.03)	0.01 (0.01)	-0.60 (-0.35)	-0.50 (-0.23)
P3	0.02 (0.07)	0.12 (0.59)	-0.16 (-0.53)	-0.29 (-0.48)	-0.78 (-1.24)	-0.44 (-0.54)	-0.07 (-0.09)	0.85 (1.03)	0.05 (0.05)	0.17 (0.17)	0.38 (0.26)	0.93 (0.52)
P4	0.14 (0.50)	0.11 (0.55)	-0.09 (-0.29)	-0.13 (-0.24)	-0.58 (-0.99)	-0.19 (0.27)	0.05 (0.07)	0.73 (0.99)	-0.09 (-0.11)	0.26 (0.27)	0.82 (0.59)	0.94 (0.50)
Overvalued	0.04 (0.17)	0.08 (0.46)	-0.15 (-0.56)	-0.30 (-0.62)	-0.73 (-1.37)	-0.27 (-0.43)	0.09 (0.13)	0.75 (1.13)	0.08 (0.11)	0.58 (0.62)	1.16 (0.91)	1.94 (1.11)
UMO	0.11 (1.06)	0.15 (1.30)	0.13 (0.93)	0.57 (1.22)	0.49 (0.91)	0.40 (0.58)	0.31 (0.46)	0.49 (0.56)	0.68 (0.68)	-0.02 (-0.03)	-1.12 (-1.31)	-2.61 (-2.31)

Panel C ample from 2009 to 2016

	K =0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	-0.04 (-0.15)	0.29 (1.30)	0.65 (1.96)	0.92 (1.78)	1.33 (2.17)	1.97 (2.18)	2.47 (2.49)	3.47 (2.56)	3.71 (3.03)	2.14 (3.84)	7.29 (3.92)	7.12 (3.13)
P2	-0.08 (-0.36)	0.32 (1.35)	0.53 (1.74)	0.62 (1.38)	1.07 (1.95)	1.74 (2.07)	2.34 (2.55)	3.00 (2.48)	3.26 (2.85)	4.56 (3.46)	6.19 (3.64)	6.82 (2.93)
P3	0.11 (-0.50)	0.25 (1.21)	0.42 (1.48)	0.41 (0.97)	0.58 (1.15)	1.10 (1.58)	1.57 (2.15)	2.05 (2.24)	2.22 (2.58)	3.31 (3.57)	4.36 (3.87)	4.69 (2.85)
P4	0.07 (-0.36)	0.20 (1.05)	0.37 (1.44)	0.36 (0.99)	0.49 (1.17)	1.03 (1.65)	1.53 (2.38)	1.88 (2.28)	2.05 (2.60)	3.23 (3.83)	4.34 (4.13)	4.98 (3.28)
Overvalued	0.11 (-0.51)	0.18 (1.03)	0.24 (1.06)	0.31 (0.88)	0.51 (1.35)	1.04 (1.83)	1.49 (2.54)	1.66 (2.20)	1.92 (2.73)	3.25 (4.27)	3.78 (3.93)	3.83 (2.96)
UMO	0.07 (0.07)	0.11 (1.27)	0.41 (2.30)	0.61 (2.35)	0.81 (1.93)	0.93 (1.69)	0.99 (1.54)	1.81 (1.89)	1.79 (2.14)	1.89 (2.02)	3.51 (2.65)	3.29 (2.29)

Table 4a. REITs Aggregate Daily Returns for Portfolios Formed Using Sorts on Premium to NAV from Green Street Advisor

This table displays the aggregate daily return of portfolios sorted by premium to net asset value. These portfolios are hold for K days. K=0 is the releasing day return. Returns are in percentage; the t-statistics are reported in parentheses. The mean premium to net asset value are reported in bracket in the first column.

Panel A: Sample from 2001-2016

	K=0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	0.02 (0.12)	0.37 (1.87)	0.42 (1.52)	0.66 (1.08)	0.63 (1.10)	1.01 (1.31)	1.33 (1.66)	2.36 (2.39)	2.20 (2.18)	2.78 (2.56)	3.64 (2.61)	5.19 (3.64)
P2	0.01 (0.04)	0.20 (1.17)	0.10 (0.39)	0.11 (0.21)	0.18 (0.35)	0.62 (0.96)	0.90 (1.31)	1.58 (1.96)	1.19 (1.44)	1.89 (2.05)	2.51 (2.56)	3.66 (3.35)
P3	0.00 (0.01)	0.27 (1.77)	0.25 (1.06)	0.10 (0.22)	0.25 (0.63)	0.64 (1.20)	0.97 (1.71)	1.56 (2.34)	1.24 (1.89)	1.97 (2.62)	2.69 (3.22)	3.87 (4.05)
P4	0.04 (0.26)	0.21 (1.44)	0.06 (0.25)	-0.03 (-0.07)	0.02 (0.06)	0.43 (0.91)	0.79 (1.65)	1.27 (2.29)	0.95 (1.69)	1.72 (2.80)	2.45 (3.48)	3.66 (4.44)
Overvalued	0.14 (0.90)	0.18 (1.39)	0.08 (0.37)	-0.01 (-0.03)	0.14 (0.40)	0.48 (1.08)	0.88 (1.81)	1.25 (2.36)	1.04 (1.90)	1.81 (2.96)	2.70 (3.87)	4.12 (5.18)
UMO	-0.12 (-1.64)	0.19 (2.00)	0.34 (2.84)	0.68 (2.17)	0.49 (1.45)	0.53 (1.12)	0.45 (0.94)	1.11 (1.73)	1.16 (1.71)	0.96 (1.39)	0.97 (1.18)	1.07 (1.18)

Panel B: Sample from 2001-2008

	K =0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	0.09 (0.30)	0.34 (1.11)	0.05 (0.12)	0.02 (0.02)	-0.43 (-0.48)	-0.14 (-0.12)	-0.06 (-0.06)	0.81 (0.62)	-0.07 (-0.05)	-0.29 (-0.20)	-0.88 (-0.53)	-0.25 (-0.13)
P2	0.14 (0.50)	0.11 (0.43)	-0.34 (-0.95)	-0.47 (-0.53)	-0.76 (-0.94)	-0.27 (-0.27)	-0.16 (-0.15)	0.67 (0.58)	-0.33 (-0.27)	-0.27 (-0.20)	-0.51 (-0.36)	-0.01 (0.00)
P3	0.09 (0.33)	0.22 (0.97)	-0.10 (-0.28)	-0.33 (-0.45)	-0.35 (-0.56)	-0.05 (-0.06)	0.09 (0.10)	0.92 (1.09)	0.03 (0.03)	0.14 (0.14)	0.10 (0.08)	0.80 (0.56)
P4	0.14 (0.53)	0.13 (0.61)	-0.28 (-0.82)	-0.42 (-0.61)	-0.55 (-0.93)	-0.08 (-0.12)	0.19 (0.25)	0.87 (1.10)	-0.01 (-0.01)	0.48 (0.51)	0.68 (0.61)	1.51 (1.14)
Overvalued	0.27 (1.18)	0.12 (0.66)	-0.20 (-0.69)	-0.43 (-0.73)	-0.38 (-0.70)	-0.06 (-0.09)	0.21 (0.30)	0.95 (1.35)	0.12 (0.15)	0.56 (0.61)	1.06 (0.96)	2.22 (1.78)
UMO	-0.18 (-2.01)	0.22 (1.42)	0.25 (1.29)	0.45 (0.89)	-0.06 (-0.11)	-0.08 (-0.11)	-0.28 (-0.42)	-0.14 (-0.17)	-0.19 (-0.20)	-0.85 (-0.99)	-1.94 (-2.22)	-2.47 (-2.55)

Panel C: Sample from 2009-2016

	K =0	1	2	5	10	15	20	25	30	40	60	80
Undervalued	-0.04 (-0.19)	0.41 (1.60)	0.81 (2.29)	1.33 (1.96)	1.68 (2.41)	2.16 (2.23)	2.70 (2.44)	3.88 (2.65)	4.45 (3.15)	5.82 (3.82)	8.15 (4.73)	10.64 (5.16)
P2	-0.12 (-0.60)	0.29 (1.25)	0.57 (1.60)	0.72 (1.36)	1.10 (1.76)	1.51 (1.76)	1.96 (2.24)	2.47 (2.22)	2.70 (2.48)	4.04 (3.25)	5.54 (4.36)	7.33 (5.50)
P3	-0.08 (-0.42)	0.33 (1.55)	0.61 (2.00)	0.55 (1.14)	0.85 (1.67)	1.33 (1.84)	1.84 (2.39)	2.19 (2.13)	2.44 (2.62)	3.78 (3.66)	5.29 (4.89)	6.94 (6.10)
P4	-0.06 (-0.30)	0.29 (1.47)	0.42 (1.49)	0.39 (0.93)	0.59 (1.38)	0.93 (1.55)	1.39 (2.28)	1.67 (2.12)	1.91 (2.51)	2.96 (3.79)	4.21 (5.18)	5.81 (6.55)
Overvalued	0.01 (0.03)	0.25 (1.27)	0.37 (1.26)	0.42 (0.96)	0.64 (1.54)	1.02 (1.68)	1.53 (2.37)	1.54 (1.95)	1.96 (2.61)	3.05 (3.86)	4.35 (5.22)	6.03 (6.86)
UMO	-0.05 (-0.46)	0.16 (1.45)	0.44 (3.16)	0.91 (2.65)	1.03 (2.27)	1.13 (1.93)	1.17 (1.70)	2.34 (2.43)	2.49 (2.60)	2.76 (2.60)	3.81 (3.01)	4.61 (2.89)

Table 5. Cross-sectional Regression of REIT Returns on Firm Characteristics

This table shows the multivariate cross-sectional regression results on firm characteristics. The dependent variables are individual REIT monthly return. Size is the begin of month market equity. BM is the last year end market equity divide last year June book value. RET2_12 is the aggregate return in the past 2 to 12 month. I2A is the annual growth rate in total non-cash assets. ROE is measured as quarterly return on equity. SUE is the standardized unexpected earnings. TN is the average daily share turnover during the past 6 month. PC_NII is the quarterly change in the number of institutional investors. P2NAV is begin of month premium to net asset value.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.013 (3.56)	0.007 (2.06)	0.009 (2.42)	0.005 (1.05)	0.007 (1.47)	0.006 (1.27)		0.014 (1.86)
SIZE		-0.001 (-1.29)	-0.001 (-0.16)	-0.001 (-1.33)	0.000 (0.02)	0.000 (-0.10)		0.000 (-0.25)
BM		0.003 (0.10)	-0.002 (-0.71)	0.002 (0.64)	0.001 (0.04)	-0.001 (-0.22)		-0.007 (-1.22)
RET2_12		0.011 (2.05)	0.017 (1.89)	0.014 (2.15)	0.012 (1.10)	0.08 (1.59)	0.0126 (1.32)	0.031 (2.19)
I2A				-0.004 (-0.11)	0.003 (0.07)	0.002 (0.54)	0.000 (-0.01)	0.004 (1.02)
ROE				0.080 (1.93)	0.089 (2.12)	0.085 (1.71)	0.122 (3.35)	0.064 (0.87)
SUE						0.000 (-0.09)	0.001 (0.29)	0.001 (0.80)
PC_NII							-0.005 (-0.37)	-0.017 (-0.99)
TN							0.183 (0.29)	-0.599 (-0.73)
P2NAV	-0.013 (1.92)		-0.019 (-3.20)		-0.020 (-3.39)	-0.018 (-2.99)	-0.019 (-3.12)	-0.018 (-2.44)
R ²	0.085	0.172	0.229	0.244	0.298	0.33	0.33	0.404

Table 6. REITs Anomaly and Premium to Net Asset Value

This table reports average return and average premium to net asset value for REIT quintile portfolios. In each month, REIT portfolios are formed by size, BM, momentum, asset growth, profitability, and earning surprise using all equity REITs. Ret (%) is the value-weighted portfolio return in percentage. P2nav_vw is the value weighted average premium to net asset value for each portfolio. P2nav_ew is the equal weighted average premium to net asset value for each portfolio. In each portfolio, N indicates the number of stocks with premium to net asset value available. t is the t-value for return difference and p2nav difference between quintile 5 and quintile 1.

Size					Book to Market				
	Ret (%)	P2nav_vw	P2nav_ew	N		Ret (%)	P2nav_vw	P2nav_ew	N
Small	0.76	-0.153	-0.172	2.0	Growth	0.68	0.092	0.058	16.9
2	0.70	-0.030	-0.039	6.9	2	0.72	0.035	0.015	14.8
3	0.66	-0.006	-0.015	12.3	3	0.57	0.010	-0.022	11.2
4	0.68	0.025	0.016	19.9	4	0.63	-0.033	-0.050	8.2
Big	0.61	0.086	0.073	24.8	Value	0.73	0.0002	-0.013	4.6
S-B	0.14	0.243	0.245		V-G	0.05	-0.092	0.072	
t	0.98	12.66	13.45		t	0.23	-12.68	-10.43	
Momentum					Return on Equity				
	Ret (%)	P2nav_vw	P2nav_ew	N		Ret (%)	P2nav_vw	P2nav_ew	N
Loser	0.51	-0.062	-0.093	8.7	Weak	0.38	-0.019	-0.047	8.8
2	0.67	0.000	-0.037	11.1	2	0.91	0.025	-0.005	13.8
3	1.12	0.047	0.009	12.5	3	0.11	0.062	0.031	14.1
4	1.13	0.097	0.058	12.8	4	0.11	0.093	0.066	32.2
Winner	1.21	0.139	0.111	10.1	Robust	1.22	0.104	0.081	12.2
W-L	0.70	0.200	0.204		R-W	0.84	0.123	0.128	
t	2.28	18.13	21.16		t	3.47	21.71	24.94	
Earning Surprise					Investment to Asset				

	Ret (%)	P2nav_vw	P2nav_ew	N		Ret (%)	P2nav_vw	P2nav_ew	
Low	0.62	0.056	0.012	10.4	Conserve	0.93	0.017	-0.026	9.1
2	0.66	0.041	0.011	10.2	2	0.96	0.032	-0.004	12.8
3	0.78	0.057	0.019	10.6	3	0.83	0.066	0.027	14.1
4	1.36	0.075	0.053	11.8	4	0.78	0.087	0.059	12.7
High	1.41	0.103	0.066	12.1	Aggressive	0.71	0.108	0.075	9.8
H-L	0.78	0.046	0.054		C-A	0.22	-0.09	-0.101	
t	3.90	8.52	9.88		t	1.10	-13.4	-18.87	

Table 7. Summary Statistic for REITs Institutional Ownership

This table reports the means, standard deviations and percentiles for the number of institutional invests(#Inst) and percentage of shares hold by institutional investors (%Inst) during the six calendar quarters before June. abs (Δ #instit) is absolute value of the number of institutional investor change. Change variables are converted to annualized equivalent values. Data are from January 1980 to Dec 2015.

Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl
#instit	87.6	92.4	13.0	58.0	138.0
%instit	43.8%	33.1%	11.8%	38.6%	73.9%
Δ #instit	19.3%	45.1%	0.0%	8.3%	24.4%
Δ %instit	0.9%	7.4%	-2.3%	0.2%	3.8%
abs (Δ #instit)	26.0%	41.6%	4.8%	12.8%	28.9%
abs (Δ %instit)	5.0%	5.5%	1.0%	3.1%	7.1%

Table 8. Change in Institutional Investor for REIT Anomaly

This table shows the changes in institutional ownership during the anomaly portfolio formation period. $\Delta\#Inst$ is the change in the number of institutional investor. $\Delta\%Inst$ is the change in fraction of shares hold by institutional investors. The changes of institutional ownership for MOM, UMO, SUE, ROE, I2A, Size, BM are the annualized 6 quarter change during the anomaly formation period. The Change of institutional owner ship for UMO1 is one quarter institutional ownership change before net asset value reporting date. UMO_means sort the portfolio based on past 3-month mean p2nav. UMO_shock represent portfolios sorted by monthly p2nav change.

		$\Delta\#Inst$	$\Delta\%Inst$		$\Delta\#Inst$	$\Delta\%Inst$
MOM	Loser (S)	0.1020	0.0003	Aggressive(S)	0.2705	0.0112
		0.1692	0.0125	I2A	0.1203	0.0082
	Winner (L)	0.2683	0.0198	Conservative(L)	0.1082	0.0114
	L-S	0.1663	0.0195	L-S	-0.1623	0.0002
		(6.46)	(7.38)		(-5.67)	(0.08)
SUE	Low(S)	0.1047	0.0058	Weak(S)	0.1330	0.0100
		0.1197	0.0066	ROE	0.2072	0.0136
	High (L)	0.1855	0.0137	Robust(L)	0.1808	0.0103
	L-S	0.0808	0.0079	L-S	0.0478	0.0003
		(4.12)	(3.62)		(2.09)	(0.11)
BM	Growth(S)	0.1586	0.0118	Big (S)	0.1478	0.0119
		0.2366	0.0099	Size	0.1862	0.0139
	Value(L)	0.1726	0.0061	Small (L)	0.2023	0.0062
	L-S	0.0140	-0.0053	L-S	0.0545	-0.0057
		(0.30)	(-0.90)		(2.42)	(-1.84)
UMO	Overvalue (S)	0.1571	0.0170	Overvalue(S)	0.0332	0.0038
		0.1342	0.0208	UMO1	0.0191	0.0031
	Undervalue(L)	0.0707	0.0062	Undervalue(L)	0.0078	0.0011
	L-S	-0.0864	-0.0108	L-S	-0.0254	-0.0027
		(-7.81)	(-2.57)		(-3.26)	(-1.67)
UMO _mean	Overvalue(S)	0.0280	0.0023	Overvalue(S)	0.0447	0.0051
		0.0198	0.0012	UMO _shock	0.0210	0.0018
	Undervalue(L)	0.0136	-0.0002	Undervalue(L)	0.0145	0.0005
	L-S	-0.0144	-0.0025	L-S	-0.0302	-0.0046
		(-3.72)	(-0.98)		(-1.88)	(-1.52)

Table 9. Institutional Investor Demand Shock and Sentiment by Volatility Quintile

This table shows the correlation between change in sentiment and change in institutional ownership. All equity REITs stocks are sorted into five portfolios based on their idiosyncratic volatility. ΔInst is the number of institutional ownership change. ΔCCI is the monthly change in consumer confidence index reported by The Conference Board. ΔMich is the monthly change of consumer sentiment index published by University of Michigan.

	$\rho(\Delta\text{Inst}, \Delta\text{CCI})$	$\rho(\Delta\text{Inst}, \Delta\text{Mich})$
Low ivol stocks	0.121 (0.15)	0.012 (0.88)
2	0.060 (0.47)	-0.043 (0.45)
3	0.121 (0.15)	-0.004 (0.95)
4	0.135 (0.11)	0.091 (0.28)
High ivol stocks	0.252 (0.01)	0.163 (0.05)

Appendix

REITs Portfolio Construction

At the beginning of each month. We sort equity REITs into five portfolios based on the following characteristic. Then we aggregate the portfolio monthly return to get portfolio quarterly return. Data used to construct portfolios can be download from CRSP and COMPUSTAT.

Market Equity (Size) is the share price times the number of shares outstanding. The market equity is calculated at the beginning of each month.

Book-to Market (B/M) is the book equity divided by market equity. The B/M is calculated at June each year. The book equity is from the end of last fiscal year. The market equity is from the end of last Calendar year.

Momentum (MOM) is measured as the cumulative return in the past t-12 to t-2 month.

Investment (I/A) is the annual growth rate in total non-cash asset. Annual investment growth rate is considered know four months after fiscal year end.

Profitability (ROE) is measured as quarterly return on equity, defined as income before extraordinary item dividend by one-quarter-lagged book equity. quarterly ROE is considered know on the earnings announcement date (RDQ).

Earnings Surprise (SUE) is measured as the standardized unexpected earnings. SUE is calculated as the change in the most recent quarterly earnings per share (EPSPXQ) from its value in the same quarter last year. Divided by the standard deviation of this change over the previous eight quarters. Earnings surprise is considered known on the earnings announcement date (RDQ).

Essay 3:

Momentum Crash and Time Variation in Value

Abstract

Despite its high profitability on average, the momentum strategy (Jegadeesh and Titman, 1993) can experience severe crashes occasionally. While previous studies often focus on the market condition (Cooper, Gutierrez, and Hameed, 2004), we study the characteristics of the momentum portfolios around the crash time. We show that the short leg of momentum strategy (the portfolio of loser stocks) tend to have extreme book-to-market ratio right before crashes. This fact helps explain why momentum crashes are often driven by the sharp rebounding of its short leg. Moreover, incorporating the book-to-market information can improve our ability to forecast momentum crashes. Our finding has two implications. First, momentum investors can improve their returns by utilizing information on stock valuation. Second, understanding what causes the extreme valuation of the short leg of momentum may shed light on the economic force behind momentum crashes.

1. Introduction

The momentum strategy first documented by Jegadeesh and Titman (1993) is very profitable. From 1927 to 2015, momentum produces an annual return of 14.5% by buying past winner stocks and selling the past loser stocks. Momentum also has higher Sharpe ratio than the market factor, as well as the size and value factors. However, momentum is more volatile and experiences severe crash occasionally. For example, from January 1928 to May 1932, the cumulative momentum return is equal to 477%. But momentum suffers large negative returns of -61% and -77% in June and July of 1932. As a result, the cumulative momentum return drops to -48%. Momentum crash also happened in 2009. From January 2005 to February 2008, the cumulative momentum return is 176%, but it drops to -30% in May 2009.

Understanding momentum crashes is important for two reasons. First, momentum crash can cause great losses for investors who implement the strategy. For example, Grinblatt, Titman and Wermers (1995) show that 77% of the mutual funds have the tendency to buy stocks based on their past returns. Thus investors can benefit if we can better understand and forecast momentum crashes. Second, studying momentum crashes could shed light on the possible source of momentum returns. Previous studies use different approaches to explain momentum. Conrad and Kaul (1998) conjecture that the momentum strategy's profitability is from the cross-sectional variability in the mean return of individual stocks; Moskowitz and Grinblatt (1999) argue that momentum is largely driven by industry factor. Daniel, Hirshleifer and Subrahmanyam (1998) follow the behavioral approach and attribute momentum to the overreaction of investors. Until now, the driving force behind momentum remains an open question.

In this paper, we study the characteristics of winner and loser portfolios and it could help us better understanding momentum crash. Stivers and Sun (2010) show that the value premium is

countercyclical and the momentum premium is procyclical. Asness, Moskowitz and Pedersen (2013) also document the negative relation between momentum factor and value factor for different markets and assets. Inspired by their findings, we investigate whether the stock valuation can be useful for modeling momentum crash. We find out that book-to-market ratio is significantly related to momentum return. The time varying Book-to-market ratio is consistent with the option like behavior (Option like behavior indicates that the loser portfolio will earn a lot when market start to rebound in bear market.) of loser portfolio documented in Daniel and Moskowitz (2015). In particular, average book-to-market ratio of the loser portfolio is high in the bear market and it becomes extremely high right before the rebound of market. These high book-to-market loser stocks will generate large positive return when market goes up. On the other hand, the book-to-market ratio of the winner portfolio does not significantly related to momentum return.

Motivated by our findings, we incorporate book-to-market ratio to forecast momentum crashes. Compare with the market past return introduced by Cooper, Gutierrez, and Hameed (2004) and the market volatility used in Daniel and Moskowitz (2015). Book-to-market ratio performs well in logistic regression model for predicting momentum crashes. The accuracy of the model (measured by area under ROC curve) when using book-to-market as independent variable is higher than the accuracy of the model when using the market volatility and market past return. When using all these three variables, the coefficient of book-to-market ratio remains significant. The market past return becomes much weaker and insignificant and the market volatility become insignificant in subsample period from 1970 to 2015.

This paper contributes to the literature on stock return momentum by documenting the important relation between momentum return and book-to-market ratio. It also shed light on how

to explain momentum return performance during crash period. Finally, it suggests potential new momentum strategy by carefully trading the high book-to-market past loser stock in bear market.

The remaining of this paper is organized as follows: Section II outlines the data and portfolio construction. Section III describes momentum crash and how it is related to book to market ratio. Section IV shows the empirical test and result. Section V discusses the industry evidence of momentum crash. Section VI concludes the paper.

2. Data and Portfolio Construction

2.1. Data

The main data source is the center for Research in Security Prices (CRSP). The sample consists of all common equity (share code equals 10 or 11) listed on NYSE, AMEX and NASDAQ (exchange code equals 1, 2 or 3). Book equity data are from U.S Book Equity Data on Kenneth French website and from Compustat annual data. Fama French three factors are from Kenneth French Data library. The whole sample period is from 1927 to 2015.

2.2. Momentum Measure

Momentum return: We follow the Fama French approach to calculate momentum return. Ten value weighted portfolio is constructed based on their past $t-2$ to $t-12$ month return. The portfolio with highest past return is called the winner portfolio; the one portfolio with lowest past return is called loser portfolio. The momentum return for each month is calculated by using winner portfolio return minus loser portfolio return. In order to reduce the influence of small stocks, the momentum returns used in this paper are all value weighted. (See appendix A for more detail about momentum return used in this paper)

2.3. Book-to-Market Measure

The major source of book equity data is U.S. Book Equity Data which downloaded from Kenneth French website. U.S. Book Equity Data (1926-2015). If U.S. Book Equity Data is missing, book equity will be constructed by using Balance sheet data from Compustat which equals shareholders' equity³, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock. The market equity data for each month are constructed by using last month end closing price multiply number of shares outstanding. When calculate book-to market ratio, book equity at fiscal year t-1 will be applied to July t to June t+1. The portfolio book-to-market ratio is calculated by using the sum of book equity divided by sum of market equity.

3. Momentum Crash and Characteristic of Winner and Loser Portfolio

Momentum experience larger and more frequent downside compare to Fama French three factors. Table 1 lists descriptive statistics for momentum and the Fama French three factors from 1927 to 2015. Momentum yield highest return of 14.54 percent per year and highest Sharpe ratio of 0.53 per year. Buying past winner and shorting the past loser provide a stable and high yield trading strategy to investors. But Momentum also has the lowest skewness and highest volatility, which could be riskier in certain time period.

[Insert Table 1 here]

Momentum does experience large crash in the past century Figure 1(top panel) shows the monthly momentum return and return distribution. Fig 1(bottom panel) shows the cumulative

³ Book equity is, depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity.

momentum return in 1930s and 2000s. Two largest momentum crashes happened in 1932 and 2008, and the previous return are all wiped out after crash.

[Insert Fig 1 here]

Momentum crash usually happened in the bear market when market start to bouncing up. Bear market is identified when past 36 month market excess return is negative. In table 3, 14 out of 15 momentum crash months happened in bear market. Table 2 also indicates that momentum return is lower and negative skewed in bear market. Furthermore, momentum crash is mainly driven by the loser portfolio. Figure 2 shows that momentum return move closely with the loser portfolio return during momentum crash period (1940s and 2010s). Table 3 lists the worst 20 momentum crash month; loser portfolio in these crash months contribute much more than winner portfolio.

[Insert Fig 2 here]

[Insert Table 2 here]

[Insert Table 3 here]

The relation between momentum and book to market ratio can be seen on Fig 3. The top two graphs show the loser portfolio return and loser book to market ratio in 1930s and 2010s. When book to market ratio is high, loser portfolio will have large positive return and cause momentum to crash. On the other hand, winner portfolio does not have any extreme returns during these periods and the relation between winner portfolio return and book to market ratio are not obvious.

[Insert Fig 3 here]

Some key facts are summarized below:

1. Momentum return is negative skewed and has high volatility
2. Momentum perform better in bull market than in bear market
3. Momentum experience crash in bull market when market start to go up
4. Momentum crash is mainly driven by loser portfolio
5. Loser portfolio has high book to market ratio during momentum crash period.

4. Model and Empirical Result

We want to test the relation between book-to-market ratio and momentum return. We especially interested in their relation during momentum crash period. Follow the approach used in Daniel and Moskowitz (2015), conditional CAPM model is constructed to see how well c book-to-market ratio explains momentum in different market state.

First consider the standard regression model,

$$WML_t = \alpha_0 + \beta_0 RM_t + \gamma_0 BM_t + \epsilon \quad (1)$$

The dependent variable WML_t used in the models is the value weighted monthly momentum return. The independent variables are: RM_t , the monthly excess return on market, and BM_t , book to market ratio of winner minus loser portfolio . Regression (4) in Tablet 4 shows the results. Consistent with previous literatures which state the negative correlation between value and momentum factor, our result indicates that book-to-market ratio and momentum are also related. The parameter for book-to-market ratio is 0.512 and statistically significant. In other words, high winner's book-to-market ratio or low loser's book-to-market ratio will relate to high momentum return. The market beta is negative and significant for the full sample.

Regression (5) in Table 4 adds a bear market indicator variable to the regression. Bear market indicator (B) equals one if past three year market excess return is positive, and equals zero otherwise.

$$WML_t = \alpha_0 + \alpha_1 B_t + (\beta_0 + \beta_1 B_t) RM_t + (\gamma_0 + \gamma_1 B_t) BM_t + \epsilon \quad (2)$$

Consistent with Cooper, Gutierrez and Hameed (2004), the market beta is -0.887 lower in bear market, and the beta is statistically significant with $t=-11.4$. The point estimates for book-to-market ratio parameter are $0.249+0.536=0.785$ and statistically significant in bear market. This indicates the high book to market has stronger effect on momentum in bear market.

Daniel and Moskowitz (2015) and Barroso and Santa-Clara(2012) both show that momentum crashes are more likely to happened in bear market when market start to go up. Regression (6) in Table 4 adds contemporaneous up market indicator variable in order to test this trend. Contemporaneous up market state indicator (U) equals one if return on CRSP value-weighted index minus risk free rate is greater than zero, and it equals zero otherwise.

$$WML_t = \alpha_0 + \alpha_1 B_t + [\beta_0 + B_t(\beta_1 + U\beta_2)] RM_t + [\gamma_0 + B_t(\gamma_1 + U\gamma_2)] BM_t + \epsilon \quad (3)$$

The result is consistent with our assumption, the parameter for book-to-market ratio (γ_2) equals one and statistically significant. γ_2 has larger magnitude compare to other parameter, which indicates high winner minus loser book to market ratio has a strong impact on momentum during momentum crash period.

Compare to Daniel and Moskowitz (2015) models which only use market state variable and market excess return, our models with book-to-market ratio has higher R-square when we estimate momentum in bear market.

We also build the same set of regression on the winner and loser portfolio of momentum separately. Regression (1), (2), and (3) in Table 5 list the regression results when using loser portfolio's book-to-market ratio to estimate momentum return. The result is consistent with the fact in part III that loser portfolio is the main driving force for momentum return; the parameter of loser's book-to-market ratio are all negative and significant which indicate that high the book-to-market ratio of loser portfolio is related to low momentum return, this trend is more obvious in bear market when market start to go up. On the other hand, regression (4), (5), (6) show that book-to-market ratio of winner portfolio do not have significant effect on momentum return.

Next we test the predicting power of book-to-market ratio for momentum crash. Wang and Xu (2015) and Daniel and Moskowitz (2015) both show that the variance of market return has predicting power for momentum. So, we build logistic regression to compare the predicting power among book to market ratio, market volatility and market return for momentum crash. A month is identified as crash month when its monthly momentum return fall in the tail 5% of the whole sample distribution from 1927 to 2015. The cut off return for the tail five percent is -10%. We also set the cut off equal -15% to construct dependent variable. Here is the logistic regression model,

$$\text{Ln} \frac{F(X)}{1-F(X)} = a + bX + \epsilon \quad (4)$$

$F(X)$ is the probability of momentum crash; X is a matrix of the predictors. X includes market excess return in past three years (MKT-3y), the realized standard deviation of daily market excess return in past 250 days (σ_{MKT}), book to market ratio of loser portfolio (L_BM).

Results are presented in table 6, the dependent variable in regression (1)-(5) use -10% monthly return as cut off for momentum crash. When test individually, market past excess return is negatively related to momentum crash which indicates that momentum crash is more likely to happen during the down market; market volatility is positive related to momentum crash which indicates that momentum crash is more likely to happen when the volatility of market is high; L_BM is negatively related to momentum crash which shows that momentum crash is likely to happen when the book to market ratio of loser portfolio is high. All of these three variables are significant and consistent with literature and our assumption. We use area under the Receiver Operating Characteristic (ROC) curve to evaluate the precision of the predicting power of these three variables. The performance of market past excess is the worst with area under ROC curve below 0.7. When use all three variable in one logistic regression model, market past return become insignificant⁴. Market volatility and book-to-market of loser portfolio remain significant for the full sample and their area under ROC are comparative. In Panel C regression (5) and (10), market volatility becomes insignificant or marginal significant when used with L_BM .

The dependent variable in regression (6)-(10) use -15% monthly return as the cut off for momentum crash. The regression results are similar to the result (1)-(5).

5. New Momentum Strategy

Using the insights form pervious sections, we design a new momentum strategy which incorporate book-to-market ratio. For each month, investor should invest w percent of their fund into the winner minus loser portfolio. W is the inverse of book-to-market ratio of the loser portfolio. The rest $(1-w)$ percent of their fund should be invested in the risk free assets or the market index.

⁴ Which variable took away the predicting power of market past return? Both book-to-market ratio of loser portfolio and market volatility do. The regression results are not shown on Tablet 6.

The performance of the different momentum strategies are summarized in Table 7. Scaling momentum by book-to-market ratio could achieve higher monthly return by 0.4% in each month. The new strategy also has lower volatility compare to the traditional momentum. By looking at the skewness and kurtosis, the new strategy has lower momentum crash risk than traditional strategy.

6. Conclusion

This paper documents the important factors which could predict the momentum crash. The book to market ratio of winner minus loser portfolio is positively related to momentum return. The book-to-market ratio of loser portfolio could explain the option like behavior of the loser portfolio in bear market. High book to market ratio in the loser portfolio will lead to a higher momentum crash probability.

For further study, it is interesting to test and compare the predicting power of other valuation measurement for momentum crash (For example: dividend yield). Moreover, it is interesting to explore momentum crash through rational approach and behavioral approach. Studying the relationship between momentum crash and Marco economic variable could shed light on the rational explanation. On the other hand, if momentum crash is highly correlated with investor's sentiment, it will be more appropriate to explain momentum crash by behavioral approach.

Appendix A. Details on How to construct Momentum portfolio.

We follow construct momentum portfolio in following step:

1. Get data from CRSP monthly stock file from 1926 to 2013
2. For each stock in month t , we clean the data by following requirements:
 - 1) CRSP sharecode equal 10 or 11(common stock);
 - 2) CRSP exchangecode equal 1, 2 or 3 (NYSE, AMEX, and NASDAQ);
 - 3) Price at month $t-13$ not missing;
 - 4) Return at month $t-2$ not missing;
 - 5) Market equity at month $t-1$ not missing
3. For each stock in month t , we calculate the cumulative monthly return for each stock from month $t-12$ to $t-2$.
4. Using the $t-2$ to $t-12$ cumulative returns of NYSE stock (exchange code=1), construct 10 decile breakpoint, and rank the whole sample by the breakpoint.
5. Calculated equal weighted return and value weighted return (use market equity at the end of month $t-1$ as weight) of each portfolio.

Our momentum return has more than 99% correlation with Kent Daniel Momentum and Fama French momentum.

Kent Daniel Momentum is from:

<http://www.kentdaniel.net/data.php>

Fama French Momentum can be found at:

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html

Table 1a. Summary Statistic for value weighted monthly momentum return from 1927-2015

Momentum	Mean	Standard		Correlation (with Fama French)
		Deviation	Sharpe Ratio	
Fama French	0.01213	0.07881	0.1129	1
This paper	0.01176	0.07897	0.1127	0.998
Daniel	0.01179	0.07862	0.1131	0.995

We compare momentum contribution instead of return is that when return is close to 0, the multiplier effect is super large.

Appendix B. Industry Evidence of Momentum Crash

Moskowitz and Grinblatt(1999) provide the evidence that Momentum is mainly driven by industry momentum which buying the past winning industry and sells the past losing industry. An interesting question is: Dose momentum crash also driven by certain industry? We keep focusing on the characteristic of loser portfolio since it is the main force for momentum crash. We classify loser portfolio into 17 industry portfolio according to Fama French Criteria. We expect to see certain industry perform differently than the other industries during the crash period.

The top graph in Fig 4 shows the standard deviation of industry return in the loser portfolio. High standard deviation of industry return indicates that some industries yield extreme monthly return compare to average industry return. The bottom graph in Fig 4 is the negative side of monthly momentum return. Their correlation is as high as 70%. In bear market, their correlation

reaches 80%. The industry contribution could be decomposed into two part, the totally market capitalization of each industry plus the average industry return. During the crash period, both of these two parts are strong for the losing industry. It is interesting to look into detail what happened in each crash and investigate the losing industry.

Table 1**Descriptive statistics of monthly data for market factor (MKT), the size factor (SMB), the value factor (HML) and the momentum factor (UMD)**

Monthly factor returns are from Kenneth French's website. The last three columns are annualized average return (%), standard deviation (%), and Sharpe ratio. The sample period is from February 1927 to July 2015.

Factor	Max	Min	Mean Return	Standard deviation	Skewness	Kurtosis	Sharpe ratio
RMRF	38.85	-29.13	7.80	18.74	0.19	7.76	0.41
SMB	36.70	-16.70	2.76	11.18	1.96	19.35	0.24
HML	35.46	-13.28	4.56	12.26	2.14	18.94	0.37
UMD	18.38	-52.26	8.28	16.45	-3.08	27.84	0.50

Table 2**Momentum returns and market state**

If the past 36-month market excess return is positive, then the current month is classified as BULL market, otherwise the current month is classified as BEAR market. The skewness and kurtosis are both calculated for winner-loser momentum return. The last column is the average book-to-market ratio of winner portfolio minus the average book-to-market ratio of loser portfolio (t-value is in parentheses).

Market State	N	Winner- Loser return	Winner-loser Skewness	Winner –Loser Kurtosis	Winner-Loser B/M
Panel A: Full sample 1927-2015					
BULL	858	0.016 (8.2)	-0.55	5.93	-0.79 (-12.7)
BEAR	186	-0.008 (-0.8)	-1.89	6.58	-2.09 (-8.8)
ALL	1044	0.011 (4.7)	-2.45	18.16	-1.02 (-15.0)
Panel B: Subsample 1927-1969					
BULL	414	0.015 (5.2)	-0.43	5.24	-1.11 (-8.4)
BEAR	90	-0.005 (-0.3)	-2.24	7.71	-3.28 (-7.9)
ALL	504	0.011 (2.9)	-3.00	23.00	-1.51 (-11.0)
Panel C: Subsample 1970-2015					
BULL	451	0.015 (5.2)	-0.92	6.02	-0.52 (-29.4)
BEAR	89	-0.007 (-0.6)	-1.72	5.03	-0.90 (-6.12)
ALL	540	0.012 (3.8)	-1.54	8.03	-0.60 (-20.5)

Table 3**Momentum returns during major crash month**

This table list 20 worst monthly momentum returns over the 1927:2-2015:7 sample period. This table also lists the winner and loser portfolio return and their book-to-market ratio. MKT is the current month market excess return.

	DATE	Winner- Loser	Loser Return	Winner Return	Market State	MKT	Loser B/M	Winner B/M
1	8/31/1932	-76.92	93.55	16.63	Bear	37.03	10.24	1.27
2	7/30/1932	-60.90	74.30	13.40	Bear	33.81	20.93	1.64
3	4/30/2009	-45.76	45.17	-0.59	Bear	10.18	6.06	0.39
4	9/30/1939	-45.19	53.07	7.88	Bear	16.87	5.63	0.72
5	4/29/1933	-43.72	70.43	26.71	Bear	38.75	10.04	1.72
6	1/31/2001	-41.87	35.83	-6.04	Bull	2.59	0.71	0.19
7	3/31/2009	-39.87	44.27	4.40	Bear	8.93	8.68	0.40
8	6/30/1938	-33.44	43.58	10.14	Bear	23.87	13.91	0.49
9	6/30/1931	-29.73	37.64	7.91	Bear	13.82	4.86	0.36
10	5/31/1933	-27.48	46.29	18.81	Bear	21.39	3.88	1.48
11	8/31/2009	-27.19	27.38	0.19	Bear	3.32	1.96	0.42
12	5/29/2009	-20.89	23.14	2.24	Bear	5.21	5.28	0.37
13	11/29/2002	-19.65	22.71	3.06	Bear	5.84	1.40	0.46
14	1/31/1975	-19.51	30.91	11.40	Bear	13.8	1.55	1.00
15	1/31/1974	-19.15	12.65	-6.50	Bear	0.46	1.22	0.52
16	4/30/1999	-18.85	17.98	-0.87	Bear	3.96	0.92	0.11
17	7/31/1973	-18.61	21.04	2.43	Bear	4.4	1.17	0.55
18	8/31/1935	-18.28	21.78	3.50	Bear	2.64	17.23	0.70
19	1/30/1932	-18.16	17.40	-0.76	Bear	-1.81	7.93	1.51
20	9/30/1970	-18.00	22.11	4.11	Bear	3.64	1.36	0.43

Table 4**Momentum return, market state and the book-to market ratio of momentum portfolio**

The table shows the parameters estimate result from monthly time-series regressions over the period 1927:2 to 2015:7 (t-value is in parentheses). The dependent variable is the value weighted momentum return. Independent variables include: The bear market indicator (B), B=1 if past three years' market return is negative; the contemporaneous up market indicator (U), U=1 if current month market return is positive; book-to-market ratio of the winner portfolio minus book-to-market ratio of the loser portfolio (B/M).

Parameter	Variable	(1)	(2)	(3)	(4)	(5)	(6)
α_0	Intercept	1.316 (5.8)	1.530 (6.6)	1.530 (6.7)	1.828 (7.4)	1.725 (6.9)	1.725 (7.0)
α_1	B		-1.534 (-2.7)	1.509 (2.0)		-0.105 (-0.2)	1.845 (2.4)
β_0	MKT	-0.541 (-13.1)	-0.142 (-2.8)	-0.142 (-2.8)	-0.519 (-12.6)	-0.132 (-2.6)	-0.132 (-2.6)
β_1	B* MKT		-0.913 (-11.7)	-0.340 (-2.8)		-0.887 (-11.4)	-0.317 (-2.4)
β_2	B*U* MKT			-0.999 (-6.0)			-0.773 (-4.3)
γ_0	B/M				0.512 (5.0)	0.249 (2.0)	0.249 (2.0)
γ_1	B* B/M					0.536 (2.6)	-0.188 (-0.7)
γ_2	B*U* B/M						1.01 (3.0)
R-square		0.14	0.16	0.25	0.16	0.27	0.29

Table 5**Momentum return, market state and book-to market of winner and loser portfolio**

This table presents the result of time-series regressions over the period 1927:2 to 2015:7 (t-value is in parentheses). The dependent variable is the momentum return. L_B/M is the book-to-market ratio of loser portfolio. W_B/M is the book-to-market ratio of winner portfolio.

Parameter	Variable	(1)	(2)	(3)
α_0	Intercept	2.127 (5.9)	1.882 (4.7)	1.882 (4.8)
α_1	B		-0.216 (-0.2)	1.245 (1.2)
β_0	MKT	-0.515 (-12.5)	-0.129 (-2.5)	-0.129 (-2.6)
β_1	B* MKT		-0.890 (-11.4)	-0.555 (-3.9)
β_2	B*U*MKT			-0.684 (-3.8)
γ_{10}	L_B/M	-0.510 (-4.97)	-0.256 (-2.0)	-0.256 (-2.1)
γ_{11}	B* L_B/M		-0.529 (-2.6)	0.316 (1.2)
γ_{12}	B*U* L_B/M			-1.180 (-3.50)
γ_{w0}	W_B/M		-0.051 (-0.08)	-0.051 (-0.08)
γ_{w1}	B* W_B/M		0.784 (0.82)	-2.834 (-2.5)
γ_{w2}	B*U* W_B/M			6.530 (5.5)
R-square		0.16	0.27	0.30

Table 6

Logistic regression result for forecasting momentum crash

Reported are logistic regression coefficient estimates (p-value in parentheses). In regression (1) -(5), the dependent variable equals one if monthly momentum return is less than -10%. In regression (6) -(10), the independent variable equals one if monthly momentum return is less than -15%. The independent variables are: Aggregate market return over the past three years (MKT-3y), the realized standard deviation of daily market excess return in past 250 days (σ_{MKT}), and the value weighted book to market ratio of the loser portfolio (L_B/M). The ROC is the area under the receiver operating characteristic curve which measures the accuracy of logistic regression.

	Momentum return <-10%					Momentum return<-15%				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Full sample 1927-2015										
Intercept	-2.48 (<0.01)	-4.22 (<0.01)	-4.00 (<0.01)	-3.36 (<0.01)	-4.22 (<0.01)	-2.98 (<0.01)	-5.30 (<0.01)	-4.81 (<0.01)	-4.14 (<0.01)	-5.19 (<0.01)
MKT-3y	-1.42 (<0.01)		-0.34 (0.33)		-0.06 (0.86)	-2.40 (<0.01)		-0.84 (0.08)		-0.33 (0.50)
σ_{MKT}		1.19 (<0.01)	1.09 (<0.01)		0.92 (<0.01)		1.47 (<0.01)	1.24 (<0.01)		1.09 (<0.01)
L_B/M				0.21 (<0.01)	0.14 (<0.01)				0.25 (<0.01)	0.16 (<0.01)
ROC	0.64	0.791	0.773	0.765	0.799	0.731	0.901	0.878	0.865	0.913
Panel B: Subsample 1927-1969										
Intercept	-2.63 (<0.01)	-4.63 (<0.01)	-4.55 (<0.01)	-3.89 (<0.01)	-5.19 (<0.01)	-3.14 (<0.01)	-5.57 (<0.01)	-5.05 (<0.01)	-4.73 (<0.01)	-6.07 (<0.01)

MKT-3y	-1.56 (<0.01)		-0.11 (0.83)		0.33 (0.49)	-2.56 (<0.01)		-0.81 (0.22)		-0.08 (0.89)
σ_{MKT}		1.32 (<0.01)	1.27 (<0.01)		1.12 (<0.01)		1.53 (<0.01)	1.25 (<0.01)		1.16 (<0.01)
L_B/M				0.23 (<0.01)	0.18 (<0.01)				0.273 (<0.01)	0.22 (<0.01)
ROC	0.702	0.815	0.812	0.819	0.844	0.785	0.902	0.878	0.942	0.943
Panel C: Subsample 1970-2015										
Intercept	-2.37 (<0.01)	-3.94 (<0.01)	-3.62 (<0.01)	-3.67 (<0.01)	-3.76 (<0.01)	-2.86 (<0.01)	-5.15 (<0.01)	-4.63 (<0.01)	-4.54 (<0.01)	-4.71 (<0.01)
Intercept	-1.32 (<0.02)		-0.65 (0.23)		-0.35 (0.55)	-2.33 (<0.01)		-1.12 (0.14)		-0.77 (0.36)
MKT-3y		1.11 (<0.01)	0.99 (<0.01)		0.50 (0.20)		1.48 (<0.01)	1.29 (<0.01)		0.85 (0.06)
σ_{MKT}				0.79 (<0.01)	0.51 (0.04)				0.89 (<0.01)	0.41 (<0.01)
ROC	0.594	0.766	0.736	0.758	0.798	0.689	0.802	0.801	0.798	0.891

Table 7**Summary statistic for plain momentum return and new momentum returns**

This table presents the summary statistics for plain winner minus loser momentum and the new momentum scaled by book-to-market ratio of loser portfolio. WML is the high minus low spread across then value-weighted portfolios sorted on past 2 to 12 month return. W is the inverse of monthly boom-to-market ratio of loser portfolio. RF is the risk-free rate. RM is the return on market index.

	Mean	Standard Deviation	Skewness	Kurtosis
WML	1.128	7.866	-2.441	18.064
$w \cdot \text{WML} + (1+w) \text{RF}$	1.563	6.875	-0.368	9.039
$w \cdot \text{WML} + (1+w) \text{RM}$	1.651	7.494	0.039	10.639

*the mean difference between new and traditional momentum strategy is statistically significant.

Figure 1. Momentum returns: The Panel A graph plots the monthly momentum return from 1927:2 to 2015:7; the Panel B plots distribution of monthly momentum return; the Panel C and D plot the aggregate momentum monthly return around the 1929 and 2008 financial crisis. Momentum returns are constructed as the high minus low spread across then value-weighted portfolios sorted on past 2 to 12 month return.

Panel A: Momentum return and its short leg return 1928-1940

Panel B: Momentum return and its short leg return 2001-2010

Figure 2. Momentum returns vs loser's portfolio returns during crash period. The solid line is the winner minus loser value weighted momentum monthly return. The dotted line is the return of its short leg (the negative return of loser portfolio).

Loser portfolio
1930-1940

Winner portfolio
1930-1940

Loser portfolio
2000-2010

Winner portfolio
2000-2010

Figure 3. Momentum portfolio returns and the book-to-market ratios. The solid lines are winner and loser portfolios returns during different time periods. The dotted lines are the normalized book-to- market ratio for winner and loser portfolios.

Panel A: Standard deviation of monthly industry contribution

Panel B: Negative part of value weighted momentum return.

Figure 4. Industry contribution and negative momentum return. The top graph plots the standard deviation of industry return contribution within the loser portfolio. For each industry within each month, Industry return contribution is calculated by using value weighted return of each industry multiplied by the total market cap of each industry divided by the total market cap of the loser portfolio. The bottom graph is the negative part of momentum return.

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