INVESTOR SENTIMENT, CREDIT AVAILABILITY, INFORMATION DISSEMINATION, AND ASSET PRICE MOVEMENTS

By

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In models of efficient financial markets, security prices represent fair valuations by rational investors, incorporate the perceived debt and equity financing costs of the marginal investor, and reflect all available public information. However, the rapid rise of asset prices in the technology sector and real estate market, liquidity crises such as those of Long Term Capital Management and Lehman Brothers, and the use of misleading information in accounting scandals such as those of Enron and WorldCom, have weakened support among economists for asset pricing models based on these fundamental determinants of value. In the following three studies, I provide evidence that behavioral factors, market frictions, and the strategic disclosure of information significantly impact asset prices.

In my first study, I examine the differential impact of investor sentiment on short- and long-run returns in public and private commercial real estate markets. In the short-run, I find evidence of sentiment-induced mispricing in both public and private real estate markets. In the long-run, however, I find a distinct difference in the time it takes prices to revert to fundamental value, as assets trading in the private market are susceptible to prolonged periods of sentiment-induced mispricing due to inherent limits to arbitrage in these markets.

In my second study, I examine the relation between credit availability, market liquidity and asset prices in both private and public commercial real estate markets. I find that changes in credit availability impact asset price movements in both private and public markets. However, I find the underlying liquidity with which these assets trade to be a key determinant of the likelihood of an asset pricing spiral, in which changes in asset prices lead to further changes in credit availability when assets are relatively illiquid.

In my final study, I examine whether the strategic disclosure of earnings guidance by firm management caters to misguided investor expectations, particularly when investors are overly optimistic. I find that firms issuing voluntary earnings guidance during periods of high investor confidence covary more with stocks that are highly sensitive to changes in investor sentiment and less with market fundamentals following the information disclosure.

CHAPTER 1
INTRODUCTION

Efficient financial markets assume that security prices represent fair valuations by rational investors, explicitly incorporate the perceived debt and equity financing costs of the marginal investor, and reflect all available public information. Any deviations in price that result from temporary changes in these fundamental determinants of value should be quickly arbitraged away by rational investors who take immediate advantage of this profit opportunity. Therefore, in an efficient market, asset price movements should be insensitive to the actions of sentiment-based investors, changes in the availability of funding for investment, and the dissemination of misleading information.

In reality, however, arbitrageurs face limitations in their ability to enter the market at precisely the time when it may be most advantageous for them to do so. For example, in response to speculative driven investment, taking the opposite side of a transaction is no longer risk-free, since sentiment-based investors introduce additional risk as they continue to bid asset prices away from their fundamental values. Furthermore, arbitrageurs may face significant funding constraints, inhibiting their ability to obtain financing for investment when it is needed most. If behavioral influences and market frictions cause prices to deviate significantly from fundamental values for prolonged periods of time, then this raises an additional concern that firms may release value-relevant information in such a manner that takes advantage of this mispricing, further exacerbating the underlying issue.

Over the past decade, the rapid rise of asset prices in the technology sector and real estate market, liquidity crises such as those of Long Term Capital Management and Lehman Brothers, and the use of misleading information that was at the heart of accounting scandals such as those of Enron and WorldCom, have further weakened support among economists for asset pricing

models based on the assumptions of efficient markets, rational expectations, and costless arbitrage. In the following three studies, I examine the impact that behavioral factors, market frictions, and information dissemination have on asset price movements in both private and public markets. In particular, I study the roles that investor sentiment, credit availability and voluntary disclosure of earnings guidance play in driving asset prices away from their fundamental values.

In my first study, I examine the differential impact of investor sentiment on both short- and long-run returns in public and private commercial real estate markets. Using vector autoregressive models to capture the short-run dynamics between returns and investor sentiment, I find a positive relation between investor sentiment and subsequent quarter returns in both public and private real estate markets. The magnitude of this short-run effect is larger in public markets than in private markets, which is consistent with private market investors being better informed and more sophisticated. This result also provides evidence on the relative importance of sentiment-driven investor demand and limits to arbitrage in asset mispricing. I further find a negative relation between investor sentiment and subsequent long-horizon public market returns, consistent with prices reverting to their fundamental values over the long-run. In contrast, I find sustained periods of sentiment-induced mispricing in private real estate markets, consistent with the significant limits to arbitrage that characterize this investment environment.

In my second study, I examine the relation between the availability of credit, market liquidity and asset price movements in both private and public commercial real estate markets. Given the relative illiquidity and significant use of leverage in acquisitions within commercial real estate markets, theory predicts that funding constraints are likely to play a significant role in asset price determination. Using vector autoregressive models to capture the short-run dynamics

between fluctuations in credit availability and price changes, I find that a tightening in credit availability is negatively related to subsequent price movements in both the private property and public REIT markets, consistent with significant leverage effects. I also find that assets trading in illiquid segments of the commercial real estate market are highly susceptible to a spiral effect, in which changes in asset prices lead to further changes in the availability of credit. In particular, I document a feedback effect of lagged price changes on subsequent capital availability in the private commercial real estate market, the lowest liquidity quartiles of the public commercial real estate market, and the relatively illiquid market for REIT preferred shares. These results suggest that while leverage plays a significant role in determining the degree to which credit availability affects asset prices, the underlying liquidity with which these assets trade is a key factor in determining the likelihood of a liquidity spiral, with lower liquidity creating the market setting for a spiral effect.

In my final study, I examine whether firm managers cater their strategic disclosure of earnings guidance to take advantage of misguided investor expectations, particularly when investors are overly optimistic. If firms issue earnings guidance that is consistent with misguided investor beliefs, voluntary disclosure of such information may contribute to sentiment-induced mispricing, rather than aid in resolving sentiment-driven overvaluation. To identify whether company issued earnings guidance impacts future asset price movements, I examine shifts in return comovement around the disclosure event. My analysis is the first to utilize voluntary disclosure events to examine sentiment-based return comovement. I find that firms issuing voluntary earnings guidance during periods of high investor confidence increase their return comovement with stocks that are highly sensitive to changes in investor sentiment and decrease their comovement with market fundamentals following the disclosure. Furthermore, I provide

evidence that this effect is concentrated around the issuance of neutral earnings guidance, which by nature contains no new information about a stock's fundamental value. This result provides further support for the sentiment-based theory of comovement.

Taken together, these three studies provide evidence that behavioral factors, such as investor sentiment, market frictions, such as a lack of liquidity or changes in the credit supply, and the strategic issuance of information, such as the voluntary disclosure of earnings guidance, can have significant impacts on asset price movements. Furthermore, these results indicate that certain market conditions, such as significant limits to arbitrage, funding constraints in relatively illiquid markets, or periods of investor optimism may act as a catalyst for non-fundamental-based pricing effects.

CHAPTER 2
INVESTOR SENTIMENT AND ASSET PRICING IN PUBLIC AND PRIVATE MARKETS

Real estate is a key input in the production process of most firms and plays a central role in economic growth and business cycles in countries around the world. Consequently, it is important to understand the sources and dynamics of real estate valuation. Although it is clear that fundamental factors influence real estate pricing, the recent well-documented bubble in U.S. housing prices, the subsequent financial crisis its "bursting" helped create, and the dramatic decline in U.S. commercial real estate prices that followed the onset of the financial crisis in 2007 have further weakened support among financial economists and practitioners for traditional asset pricing models based on the assumptions of efficient markets, rational expectations, and costless arbitrage.

A growing behavioral economics and finance literature acknowledges that economic agents are not the "hyper-rational automatons" the efficient market hypothesis assumes them to be.[1] Rather, the emerging behavioral approach recognizes the bounded rationality and psychological biases of investors who often rely on and are influenced by computational shortcuts, heuristics, frame dependence, and intuition when making decisions in a complicated and uncertain world with market frictions.[2] As a result, changes in asset prices may be driven by more than changes in market fundamentals as shown theoretically by De Long, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997), among others. Recent empirical research in behavioral finance also suggests that this movement away from fundamentals encompasses the influences of investor sentiment on asset valuation, where

[1] Bernstein (2007) attributes the term "hyper-rational automatons" to Richard Thaler.

[2] Barber and Odean (2008), for example, find that unlike institutional investors, individual investors are more prone to buy stocks that have recently been in the news.

investor sentiment is defined by Baker and Wurgler (2006, 2007) as a misguided belief about the growth in future cash flows or investment risks (or both) based on the current information set.

The empirical literature on investor sentiment and asset pricing has largely focused on public stock markets. This focus is understandable given the difficulties associated with obtaining return information on private equity investments since private equity has historically been exempt from public disclosure requirements (Kaplan and Schoar, 2005). Nevertheless, private investment markets provide an appealing testing ground for examining sentiment's pricing role. Relative to more liquid public markets, private investment markets exhibit significant information asymmetries and illiquidity. The lack of continuous price revelation in private markets suggests the potential impact of investor sentiment on market values may be revealed with significant lags.

Sentiment-induced asset mispricing arises from a combination of sentiment-driven investor demand and limits to arbitrage. Thus, the degree to which private markets are affected by investor sentiment is not ex ante clear. To the extent that private market investors are better informed and more sophisticated, asset prices could potentially be less prone to the influence of investor sentiment in these markets. However, the illiquidity, information asymmetries, and more limited price revelation inherent in private markets may allow sentiment to play a more persistent role in pushing asset prices away from their fundamental values. Moreover, the inability to short-sell in private markets impedes the opportunity for informed arbitrageurs to counteract mispricing.[3] In contrast, price revelation occurs more rapidly in public stock markets where the ability of informed investors to short-sell exists, albeit with limits. Therefore, the reversion of

[3] The limited arbitrage literature suggests that assets that are more difficult to arbitrage have potentially larger initial mispricing and then larger subsequent abnormal returns as prices revert to fundamentals (e.g., Pontiff, 1996, 2006; and Wurgler and Zhuravskaya, 2002). However, with more sophisticated investors, it is not ex ante clear that the limited arbitrage effect would lead to greater initial mispricing and greater subsequent reversals.

prices to fundamental values should occur more quickly in public markets. Despite the potential importance of investor sentiment in the price formation process, no previous research has directly investigated the relative importance of sentiment in public and private asset markets or the relative importance of sentiment-driven investor demand and limits to arbitrage in determining asset prices within each market.

In this paper, I examine the relation between investor sentiment and returns in both public and private commercial real estate markets. In my empirical tests, I use both direct (survey-based) and indirect (derived from multiple indirect sentiment proxies) real estate sentiment measures. I first examine the time-varying relation between these two sentiment measures, their relation with stock market sentiment, and their unconditional relation with public and private real estate returns. I then test the conditional short- and long-run effects of real estate investor sentiment on both public and private real estate returns. This analysis of private and public markets provides evidence on the relative importance of sentiment-driven investor demand and limits to arbitrage in asset mispricing. I also provide a unique side-by-side comparison of sentiment's short- and long-run impact on similar assets that are owned and traded in two distinct investment environments.

The commercial real estate market provides an appealing testing ground for examining sentiment's pricing role for several reasons. First, private real property markets exhibit the segmentation, information asymmetries, and illiquidity that characterize other private markets. Second, unlike other private markets, several representative total return indices for private commercial real estate are available, permitting the calculation of time-weighted returns that can be compared directly to corresponding returns in public real estate markets. Finally, the underlying properties held by the publicly traded real estate firms I analyze are similar to the

property holdings of the institutional real estate investors whose private market returns I also track. Since I also control for the additional equity characteristic embedded in the public real estate market returns, disparities in sentiment's effects on returns in public and private real estate markets can be ascribed to differences in the characteristics of these two markets, not to fundamental differences in the types of assets owned.

Initial stock and real estate market sentiment results provide evidence suggesting that investors view commercial real estate and the general stock market as distinct asset classes. The time-varying results also suggest that as the recent subprime mortgage crisis unfolded, sentiment in the commercial real estate market turned sharply downward in 2007. Real estate investor sentiment appears to have led the significant decline in property prices that occurred after the most recent peak. In contrast, stock market sentiment was slower to decline and fell less precipitously during this latter period.

Using vector autoregressive (VAR) models in which commercial real estate returns and sentiment are specified as endogenous variables in a two equation system that also includes exogenous control variables, I first address two questions: Do changes in investor sentiment predict short-run returns? And, second, do returns predict short-run changes in sentiment? Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that overconfident investors form optimistic expectations about the future value of an asset and tend to disregard information that contradicts these beliefs due to self-attribution bias. Welch (1992) also establishes a cascade model in which investors base their decisions on observations of previous market demand and ultimately ignore their own private information. Froot, Scharfstein, and Stein (1992) posit that short-horizon investors often focus on recent market demand rather than focusing on

long-horizon fundamentals, even if such demand is a "noisy" signal driven by a bewildering array of rumors, vague and incomplete information, and uncertainties.[4]

In each case, investors act on noisy information, creating momentum that ultimately pushes prices away from fundamental value over short-horizons. Therefore, I expect to observe persistence in my measures of sentiment as the expectations of sentiment-based investors are influenced by prior periods of high or low sentiment. I also expect a positive relation between sentiment and subsequent short-run returns as sentiment-driven demand, accompanied by limits to arbitrage, temporarily drive prices away from their fundamental value. However, it is plausible for the magnitude of the short-run sentiment effect on prices to be smaller (or possibly zero) in private markets than in public markets to the extent that potentially sophisticated private market investors offset the greater limits to arbitrage inherent in private markets.

I next examine whether a negative relation exists between investor sentiment and subsequent long-horizon returns in public and private commercial real estate markets. If excessive investor optimism (pessimism) leads to market overvaluation (undervaluation), then periods of high (low) sentiment should be followed by low (high) cumulative long-run returns as the market price reverts to its fundamental value in the long-run. Moreover, given the greater limits to arbitrage, short-sale constraints, information externalities, and delays in information transmission that characterize private real estate markets, I expect the impact of investor sentiment on market values in private real estate to be more persistent in pushing asset prices away from their fundamental values over time.

[4] Lamont and Thaler (2003a) provide an alternative explanation in which the marginal market participant is a sentiment-induced investor. They argue that if optimists are willing to bid up the prices of some stocks and not enough investors are willing to meet that demand by selling short, the optimists will set the price.

In my short-run analysis, I find a positive relation between investor sentiment and subsequent quarter returns in both public and private real estate markets. That is, sentiment-based investment drives prices away from fundamental value in the short-run, resulting in a short-term continuation of returns. For a given change in sentiment, the magnitude of this short-run effect is larger in the public than in the private real estate market. This result is consistent with private market investors being better informed and more sophisticated, and consequently provides evidence on the relative importance of market participant demand and arbitrage costs in asset mispricing. I also find that the effects of sentiment on asset prices are conditional on the level of sentiment. In particular, if sentiment is more than one standard deviation above average, subsequent public and private real estate returns are on average lower, which is consistent with Baker and Wurgler (2007).

Using long-horizon regressions, I also provide evidence that limits to arbitrage play an important role in determining the time it takes for prices to revert to fundamental values. In public real estate markets, periods of sentiment-induced mispricing are quickly followed by price reversals. For example, I find that an increase in investor sentiment results in a 2.9% decrease in public real estate market returns over the following year. In contrast, private real estate markets are more susceptible to prolonged periods of sentiment-induced mispricing. I find that an increase in investor sentiment results in a 3.9% increase in private real estate market returns over the subsequent year, and that this mispricing continues to persist over longer horizons.

Measuring Investor Sentiment

Prior research uses several approaches to quantify investor sentiment. One stream of research focuses on direct sentiment measures, such as survey-based measures developed to capture the outlook of market participants. Qiu and Welch (2005) provide a comparison of several direct survey-based measures of investor sentiment. An alternative stream of research

uses multiple indirect sentiment proxies for investor sentiment. Although no single measure is a pure indicator of investor sentiment, each imperfect proxy is likely to contain a sentiment component. Baker and Wurgler (2006, 2007), for example, utilize principal component analysis to develop an indirect measure of investor sentiment from multiple indirect proxies.[5] I employ both indirect and direct measures of investor sentiment in my analysis.

An Indirect Index of Real Estate Sentiment

Following the framework of Baker and Wurgler (2006, 2007), I use principal component analysis to construct an indirect quarterly sentiment index based on the common variation in seven underlying proxies of investor sentiment in commercial real estate markets: (i) the average REIT stock price premium to net asset value (NAV), (ii) the percentage of properties sold each quarter from the National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index (NPI), (iii) the number of REIT IPOs, (iv) the average first-day returns on REIT IPOs, (v) the share of net REIT equity issues relative to total net REIT equity and debt issues, (vi) net commercial mortgage flows as a percentage of GDP, and (vii) net capital flows to dedicated REIT mutual funds.

Lee, Shleifer, and Thaler (1991) suggest that closed-end fund discounts represent movements in stock prices away from fundamental values. Similarly, REIT price premiums relative to NAVs measure the difference between the market price of a REIT's shares and the estimated net asset value of the underlying properties that comprise the REIT. Stock price deviations from NAV may, in part, reflect the price impact of sentiment-based trading during periods of investor optimism or pessimism. Therefore, I obtain the average quarterly U.S. REIT price premium to NAV from Green Street Advisors, a prominent buy-side REIT advisory firm.

[5] Baker, Wurgler, and Yuan (2009) also utilize this methodology to create local and global sentiment indices across six major international stock markets.

Baker and Stein (2004) argue that aggregate market liquidity can serve as a sentiment proxy. In a market with short sale constraints, sentiment driven investors are more likely to participate when they are optimistic; therefore liquidity will likely increase during periods of investor overconfidence. I use the percentage of properties sold from the NPI each quarter as a proxy for aggregate liquidity in the private commercial real estate market.

The market timing of IPOs and secondary equity offerings have been used to measure investor sentiment in the general stock market (e.g., Ritter, 1991; Baker and Wurgler, 2000). Similarly, the number of REIT IPOs, the average first-day returns on REIT IPOs, and the share of net REIT equity issues relative to the total capital raised by REITs may identify periods of sentiment-induced mispricing in commercial real estate markets. The number of REIT IPOs and average first-day returns are constructed using data provided by the National Association of Real Estate Investment Trusts (NAREIT). The share of REIT equity issues relative to total REIT equity and debt offerings is constructed from data obtained from the Federal Reserve Flow of Funds Accounts.

Clayton, Ling, and Naranjo (2009) argue that net commercial mortgage flows are widely viewed by industry participants as a barometer of investor sentiment, in part because of the association between past real estate cycles and excessive mortgage flows during periods in which default risk may have been underpriced by lenders. Therefore, periods of increased commercial mortgage flows may reflect the influence of investor sentiment. Quarterly commercial mortgage flows are obtained from the Federal Reserve Flow of Funds Accounts and then scaled to be a percentage of GDP.

Finally, Brown et al. (2002) and Frazzini and Lamont (2008) suggest that flows into and out of mutual funds proxy for investor sentiment. Therefore, shifts in capital flows to dedicated

REIT mutual funds may indicate periods of investor over- or under-confidence. The quarterly flow of investment capital into, and out of, dedicated REIT mutual funds is obtained from AMG Data Services.

The top panel of Table 2-1 contains summary statistics for each indirect commercial real estate sentiment proxy. Note that there is substantial variation both within and across the indirect proxies. Along with this variation, however, there is also substantial persistence in the levels and changes in the indirect proxies. Utilizing quarterly data from 1992:Q2 to 2008:Q4, I generate a composite indirect real estate sentiment index (INDRES) based on the first principal component of the contemporaneous levels of each of the seven sentiment proxies.[6] INDRES is standardized to have a mean of zero and unit variance. The quarterly serial correlation of INDRES is 0.73; the serial correlation of quarterly changes in INDRES is -0.29.

A Direct Measure of Real Estate Sentiment

In addition to indirect measures of investor sentiment, the equity market sentiment literature has also used various survey-based measures to capture investor sentiment. For example, Brown and Cliff (2004, 2005) use the "bull-bear" spread, defined as the percentage of stock investment newsletters deemed to be bullish minus the percentage categorized as bearish, as classified by Investors' Intelligence.[7] Brown and Cliff (2004, 2005) relate the bull-bear spread to deviations from fundamental values and examine both short- and long-run effects of sentiment on stock returns. The authors find that the bull-bear spread is highly correlated with contemporaneous stock returns but has little short-run predictive power (Brown and Cliff, 2004).

[6] I detrend the commercial mortgage flow series using the prior 2-year rolling average before including it in my principal component analysis.

[7] Other direct measures of investor sentiment include, for example, the Michigan Consumer Confidence Index and the UBS/GALLUP Index of Investor Optimism.

However, taking a longer term perspective of two-to-three years, periods of high sentiment are followed by low returns as stock prices mean revert (Brown and Cliff, 2005).

Along similar lines, I employ survey data published by the Real Estate Research Corporation (RERC) in its quarterly Real Estate Report as a direct measure of investor sentiment in commercial real estate markets. RERC surveys institutional real estate investors, appraisers, lenders, and managers throughout the United States to gather information on current investment criteria, such as required rates of return on equity, expected rental growth rates, and current "investment conditions," the latter of which is of particular interest in this study. RERC survey respondents are asked to rank current investment conditions for multiple property types, both nationally and by metropolitan area, on a scale of 1 to 10, with 1 indicating "poor" investment conditions and 10 indicating "excellent" conditions for investing. This sentiment measure is similar in spirit to the bull-bear spread in that it captures movements in the proportion of participants in commercial real estate markets who are bullish relative to those less optimistic about current investment opportunities.[8]

The middle panel of Table 2-1 contains summary statistics on the property type components of the national level RERC investor sentiment index. Note that over the 1992:Q2 to 2008:Q4 sample period the consensus opinion of survey respondents was that apartment and industrial warehouse properties, with an average investment conditions rank of 6.3, were considered to be the most desirable, followed by neighborhood retail properties. In contrast, retail power centers, with a mean investment conditions ranking of 5.0, were deemed the least desirable investments of the eight property types over the study period. Similar to the indirect

[8] RERC also collects other investment condition variables in their survey, such as the percentage of respondents who give a buy recommendation and the percentage who give a sell recommendation. However, these variables are only available for a shorter sub-sample beginning in the latter half of the 1990s. Moreover, the correlation of RERC's buy-sell recommendation and investment conditions variables is high over the shorter sub-sample (0.77 for the direct measure that I use).

sentiment proxies, RERC's investment condition rankings display significant time variation over the sample period. For example, the investment desirability of suburban office properties ranged from a low of 2.8 to a high of 7.5. It is also important to note that RERC investment conditions display substantial positive serial correlation across quarters, with changes displaying significant negative serial correlation.

The direct measure of commercial real estate sentiment (DRES) is constructed from the first principal component extracted from quarterly RERC investment condition survey responses pertaining to the eight RERC property types.[9] DRES is standardized to have a mean of zero and unit variance. The quarterly serial correlation of DRES is 0.81; the serial correlation of quarterly changes in DRES is -0.35.

Panel A of Figure 2-1 plots DRES against INDRES over the sample period. Overall, the correlation between the two sentiment indices is 0.48 as shown in Table 2-3. During the early-to-mid 1990s, as the commercial real estate market was emerging from a downturn in the late 1980s, INDRES (the dashed line) was somewhat more volatile than DRES (the solid line). After peaking at a higher level than DRES in early 1998, INDRES dropped more precipitously during the subsequent slowdown that occurred in commercial real estate markets in the late 1990s and early 2000s. The private commercial real estate market began what became a prolonged bull market around 2003. It is interesting to note that the indirect measure of commercial real estate sentiment stabilized and then turned upward sooner than did the survey-based measure of sentiment. The significant and sustained run up in commercial property prices finally peaked in late 2007 in most U.S. markets. However, both measures of sentiment leveled out and then began to decline much earlier than transaction prices. That is, investor

[9] The correlation between an equally weighted average investment condition across the eight RERC property types and *DRES* is 0.93 over the sample period.

sentiment appears to have led the significant decline in property prices that occurred after the most recent peak.

An Indirect Index of Stock Market Sentiment

Following Baker and Wurgler's (2006, 2007) framework, I construct an indirect measure of investor sentiment for the general stock market. In particular, I utilize principal component analysis to generate a quarterly sentiment index based on the common variation in six underlying proxies of investor sentiment in the stock market: (i) the closed-end fund discount, (ii) share turnover on the NYSE, (iii) the number of IPOs, (iv) the average first-day returns on IPOs, (v) the share of equity issues in total equity and debt issues, and (vi) the dividend premium.

I update Baker and Wurgler's (2007) dataset through 2008 using the following variable definitions consistent with their study. The closed-end fund discount is defined as the difference between the net asset values (NAVs) of closed-end stock fund shares and their market prices as reported in the Wall Street Journal.[10] Share turnover on the NYSE is defined as the total volume of NYSE Group Shares divided by shares outstanding as reported in the NYSE Fact Book.[11] I obtain the number of IPOs and the average first-day returns on IPOs from Professor Jay Ritter's website. The share of equity issues in total equity and debt issues is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance as reported in the Statistical Supplement to the Federal Reserve Bulletin. The dividend premium is defined as the log difference of the average market-to-book ratios of dividend payers and non-payers (Baker and Wurgler, 2004). The bottom panel of Table 2-1 contains summary statistics for each indirect

[10] I compute the value-weighted average discount on closed-end funds classified as General Equity Funds in the Wall Street Journal.

[11] The turnover measure is expressed as the natural log of the turnover ratio and is detrended using a 5-year moving average.

sentiment proxy pertaining to the general stock market. Summary statistics for these variables are of similar magnitude to those reported in Baker and Wurgler (2007).

Utilizing data from 1965 to 2008, I generate a composite indirect stock market sentiment index (INDSMS) based on the first principal component of the contemporaneous levels or lags of each of the six sentiment proxies. The index is standardized to have a mean of zero and unit variance for the period 1965 to 2008. Table 2-2 and Table 2-3 contain descriptive statistics and correlations, respectively, for the two real estate sentiment indices as well as the stock market sentiment index over the 1992:Q2 to 2008:Q4 sample period. The mean of INDSMS is 0.43 over the sample period. The quarterly serial correlation of INDSMS is 0.76 when expressed in levels and -0.14 when expressed in changes.

Panel B of Figure 2-1 plots INDSMS against INDRES over the 1992:Q2 to 2008:Q4 sample period. Overall, the correlation between the two indices is -0.194 (Table 2-3), suggesting that investors view commercial real estate and the general stock market as distinct asset classes. Note that the divergence between the two indices beginning in 1999 coincides with the internet bubble, where investor stock market sentiment was very optimistic and real estate market sentiment was more pessimistic. During this period, many investors were shifting their holdings out of value-oriented investments, including commercial real estate, into high growth technology stocks. As the technology bubble burst and the Federal Reserve acted to avoid a recession in the wake of 9/11, real estate and other value investments became popular alternatives for investors seeking safer investment options. However, as the recent subprime mortgage crisis unfolded, sentiment in the commercial real estate market turned sharply downward in early 2007. In contrast, stock market sentiment was slower to decline and fell less precipitously during this latter period.

Empirical Methodology

Short-Run Regressions

To capture short-term sentiment and return dynamics, I employ vector autoregressive (VAR) models. In its simplest form, a VAR model is composed of a system of regressions where two or more dependent variables are expressed as linear functions of their own and each other's lagged values, as well as exogenous control variables. In more technical terms, a vector autoregression model is the unconstrained reduced form of a dynamic simultaneous equations model. An unrestricted p^{th}-order Gaussian VAR model can be represented as:

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_k Y_{t-p} + \varepsilon_t \qquad (2\text{-}1)$$

where Y_t is a vector of variables, μ is a p x 1 vector of intercepts, $\Phi_1, \Phi_2, \ldots, \Phi_k$ are p x p matrices of parameters with all eigenvalues of Φ having moduli less than one so that the VAR is stationary, and e_t is a vector of uncorrelated structural shocks [$\sim$ NID(0,Ω)]. In a bivariate framework consisting of only sentiment and returns as endogenous variables, the diagonal coefficients of Φ represent conditional momentum in sentiment and returns, while the off-diagonal coefficients of Φ represent conditional positive feedback trading (sentiment following returns) and conditional anticipation effects (returns following sentiment). The off-diagonal elements of Ω capture the price-impact effect of sentiment on returns.

I obtain maximum likelihood estimates of Φ and Ω using iterated least squares. The number of quarterly lags is chosen based on examination of the AIC, SBIC, and the likelihood ratio selection criteria for various choices of p. It is important to note that the inclusion of lagged returns in the private market return equation controls for the well-documented autoregressive nature of NCREIF returns.

I first use an unconstrained VAR system to examine the dynamic relation between direct and indirect indices of commercial real estate sentiment over the 1992:Q2 to 2008:Q4 sample period. I then examine the relation between indirect measures of real estate and stock market sentiment. Finally, I examine the relations between sentiment and real estate returns in public and private markets. To measure returns on commercial real estate, I use public U.S. equity REIT and private NCREIF returns. To measure investor sentiment, I use both INDRES and DRES. To control for stock market sentiment, I utilize the indirect general stock market index (INDSMS). Similar to Brown and Cliff (2005), I specify sentiment measures in both levels and changes within the regression framework. To control for other potential sources of variation in returns and sentiment, I also include lagged values of several control variables that have been shown to matter in the asset pricing literature as explained further in the data section.

Long-Horizon Regressions

Following Brown and Cliff's (2005) framework, I regress future k-period quarterly returns on a vector of control variables, z_t, and a measure of investor sentiment, S_t,

$$(r_{t+1} + \ldots + r_{t+k})/k = \alpha(k) + \theta(k)\, z_t + \beta(k)\, S_t + \varepsilon_t \qquad (2\text{-}2)$$

where r_{t+1} ... r_{t+k} are quarterly log returns, k is the number of quarters over which the investment horizon spans, and α is the intercept term. I include the same set of control variables in the long-horizon framework as I employ in the short-run VAR framework. If periods of optimistic (pessimistic) sentiment lead initially to overvaluation (undervaluation), then periods of high (low) sentiment should be followed by low (high) cumulative long-run returns as prices revert to their fundamental values over time. Thus, a negative coefficient on S_t in the long horizon regressions is consistent with the price reversion that occurs following the initial impact of sentiment on asset prices. However, if sentiment's effect is persistent, this would result in a positive coefficient on S_t, indicating a continuation of short-term investment returns as asset

prices either continue to move away from fundamental value or are slower to revert over longer horizons.

Several econometric issues arise from the use of long-horizon regressions. The first issue stems from the presence of overlapping observations in the dependent variable of the regression specification. Because the dependent variable consists of average long-horizon returns calculated over consecutive quarters, there will be a moving average process in the error term. Thus, the use of OLS will lead to standard errors that are biased downwards. Conventional corrections such as the methodology proposed by Hansen and Hodrick (1980) or a related procedure outlined by Newey and West (1987) are not appropriate in the present context because both procedures have been shown to exhibit poor finite sample properties, especially when serial correlation is high, as is the case with overlapping return observations. Moreover, a number of studies have documented a sizeable bias in the error term as the sample size decreases and autocorrelation in the error term increases.[12]

A second issue that arises within a small sample setting is the potential for finite sample bias in the coefficient estimate of a persistent independent variable. Stambaugh (1999) shows that a persistent explanatory variable will be predetermined but not strictly exogenous; thus, coefficient estimates may suffer from significant finite sample bias. Although an OLS estimate is consistent and asymptotically normally distributed under the predetermined assumption, it is not necessarily unbiased in finite samples. In empirical applications, this bias reduces to zero as the sample size approaches infinity. However, the coefficient estimate on a persistent investor sentiment measure may exhibit finite sample bias using quarterly observations that decrease in number as the length of the return horizon increases.

[12] See Nelson and Kim (1993), Goetzmann and Jorion (1993), and Hansen and Tuypens (2004) for further discussion of the effects of small sample bias in long-horizon return regressions.

To address the econometric issues of potentially biased coefficient estimates and standard errors that arise from the use of long-horizon regressions, I use a bootstrap simulation procedure similar to Brown and Cliff (2005). See Appendix for details.

Data and Descriptive Statistics

Return Data Sources and Definitions

Public commercial real estate returns are obtained from the CRSP/Ziman database, which is produced jointly by the Center for Research in Security Prices at the University of Chicago and UCLA's Ziman Center for Real Estate. The CRSP/Ziman database includes all REITs that have traded on the NYSE, Amex, and Nasdaq exchanges since 1980. Ownership of REITs on each of these exchanges has historically consisted of a combination of retail and institutional investors. It is interesting to note that the institutional ownership of REITs was on average lower than that of all other publicly traded stocks on each of these exchanges during the first half of the sample period (Chan, Erickson, and Wang, 2003), but has grown substantially in more recent years. Daily and monthly return indices are computed with both equal- and value-weighting for all U.S. REITs and for subsets defined by type of REIT (equity, mortgage, and hybrid) and by type of property. I use the value-weighted aggregate U.S. equity REIT index to construct a quarterly return series; thus, REITs that invest significantly in mortgages are excluded.

Return data for private real estate markets is provided by NCREIF, a not-for-profit institutional real estate industry association. Established in 1982, NCREIF collects, processes, validates, and disseminates information on the risk/return characteristics of commercial real estate assets owned by institutional (primarily pension fund) investors. NCREIF's flagship index, the NCREIF Property Index (NPI), tracks the quarterly total return performance of a large pool of individual commercial real estate properties acquired in the private market for investment

purposes only.[13] To be included in the NPI, the data contributing member's property must be at least 60% leased and be wholly owned or in a joint venture structure. Although levered properties are included in the NPI, investment performance is reported by NCREIF on an unlevered basis. The property composition of the NPI changes quarterly as data contributing NCREIF members buy and sell properties. However, all historical property-level data remain in the database and index. The average holding period of the properties included in the NCREIF database is approximately 11 years (Fisher and Young, 2000). Each property's quarterly return is weighted by its estimated market value relative to the total market value of the properties that comprise the NPI.

The NCREIF NPI is the only source of consistently collected information on the total returns earned by investors in private U.S. commercial real estate markets and is therefore widely used as a benchmark return index. Nevertheless, the NPI has several shortcomings (Geltner and Ling, 2007).[14] For example, unless the underlying property is sold during the quarter, the NPI uses changes in appraised values to calculate the appreciation component of the property's total return. The use of appraisal values may lead to "smoothing" in the index. However, smoothing in the construction of the NPI should not affect the validity of my empirical results, as the short-run VAR methodology includes lagged values of the index as explanatory values and the long-horizon regressions make use of bootstrapping adjustments. However, as a robustness check, I also use a variant of the NPI that is based on the transaction prices of index properties that sold during the quarter and obtain similar results.

[13] At the end of the fourth quarter of 2008, the NPI database contained 6,287 properties with an estimated market value of $305 billion.

[14] Also see Pagliari, Scherer, and Monopoli (2005) for a detailed description of the NCREIF NPI index.

Control Variables

To control for other potential sources of variation in returns and sentiment in both the VAR and long-horizon regression specifications, I include the following macroeconomic variables that have been shown to affect asset returns: the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSP), the spread between yields on BAA rated and AAA rated corporate bonds (DEFAULTSP), and the rate of inflation (INFLA) (e.g., Chen, Roll, and Ross, 1986; Ferson and Harvey, 1991; Fama and French, 1993; Fama and Schwert, 1977; Sharpe, 2002). I also include the three Fama-French risk factors: MKT, SMB, HML, augmented by the return momentum factor, UMD (e.g., Fama and French 1996; Liew and Vassalou, 2000; Lettau and Ludvigson, 2001; Jegadeesh and Titman, 1993; and Carhart, 1997).[15] These factors also control for the equity characteristic embedded within the public market real estate returns (e.g., Riddiough, Moriarty, and Yeatman, 2005, and Pagliari, Scherer, and Monopoli, 2005).

Descriptive Statistics

Table 2-4 reports descriptive statistics for the two primary aggregate real estate return series and control variables. As documented in the real estate literature, average total returns on publicly traded REITs typically exceed returns on similar institutional quality assets owned and managed in private markets, albeit with greater volatility. However, according to NAREIT, equity REITs produced total returns of -17.8% in 2007 and -37.8% in 2008, both of which are significantly below the comparable total returns on the NPI Index.[16] As a result, quarterly REIT returns averaged just 0.90% from 1992:Q2 to 2008:Q4 sample period. The corresponding

[15] In robustness tests, I also include Pastor and Stambaugh's (2003) liquidity risk factor and REIT dividend yields as additional control variables. The magnitude of the coefficient estimates and statistical significance of the sentiment measures remain similar.

[16] The aggregate NAREIT equity total return index is highly correlated (ρ=0.99) with the CRSP/Ziman equity index.

average NPI return is 2.3% per quarter. At 2.0%, the standard deviation of quarterly NPI returns is somewhat lower than the 2.8% standard deviation of REIT returns. The quarterly serial correlation of REITRET over the sample period is -0.04. In contrast, the serial correlation of NPIRET is 0.72, which is indicative of the return "smoothing" of the NPI index.

What about the contemporaneous correlations between sentiment and returns? In Panels A and B of Figure 2-2, I plot REIT total returns against INDRES and DRES, respectively, over the sample period. Sentiment is measured on the left vertical axis, while quarterly REIT returns are measured on the right. Recall that sentiment indices are constructed to have a mean of zero and unit variance. In Panels C and D of Figure 2-2, I plot NPI returns against INDRES and DRES, respectively.

Inspection of Panels A and B of Figure 2-2 does not reveal a consistent contemporaneous univariate relation between either of the sentiment measures and REITRET. However, there are several periods, including 2006 to 2008, during which the sentiment measures and REIT returns do appear to move together. This comovement is reflected in a contemporaneous correlation of 0.46 between REITRET and INDRES over the full sample period. The contemporaneous correlation between REITRET and DRES (Panel B of Figure 2-2) is 0.34.

Panels C and D of Figure 2-2 reveal that, relative to Panels A and B, private real estate returns appear to better track movements in sentiment than do REIT returns. This is confirmed by a contemporaneous correlation between INDRES and NPIRET of 0.43 (Panel C); the correlation between DRES and NPIRET is 0.57 (Panel D). I also observe this positive relation between private market returns and lagged direct sentiment in both the VAR and long-horizon regression models.

Short-Run Regression Results

Dynamic Relations amongst Sentiment Measures

Table 2-5 provides estimates of unconstrained VAR models with two measures of investor sentiment specified as endogenous variables and the following exogenous control variables: TBILL, TERMSP, DEFAULTSP, INFL, MKT, SMB, HML, and UMD. The sample period is 1992:Q2 to 2008:Q4. The first set of VARs (reported in columns 1 through 4) quantifies the relation between INDRES and DRES, expressed in levels and changes, respectively, over the 1992:Q2 to 2008:Q4 sample period. Previously, I documented a strong positive contemporaneous correlation between INDRES and DRES (ρ=0.48). However, inspection of Table 2-5 reveals that lagged DRES does not explain variation in indirect sentiment regardless of whether INDRES is specified in levels or changes. In the INDRES equation, the estimated coefficient on $INDRES_{t-1}$ is positive and highly significant, consistent with the high serial correlation of INDRES. Changes in INDRES (column 3) are negatively related to lagged changes in INDRES. In the DRES and ΔDRES equations (columns 2 and 4), I find similar results; that is, lagged INDRES does not explain current levels or changes in DRES. Rather, the variation in DRES and ΔDRES is explained by lagged values of DRES. It is important to emphasize that, although not reported in Table 2-5, macroeconomic control variables do not explain the variation in either sentiment measure. That is, both INDRES and DRES capture investor sentiment unrelated to market fundamentals.[17]

The second set of VARs (columns 5 through 8 in Table 2-5) examine the dynamic relation between INDRES and general stock market sentiment (INDSMS). Previously, I documented a contemporaneous correlation of -0.194 between INDRES and INDSMS, suggesting investors

[17] In all specifications, I fail to reject the null hypothesis that the set of exogenous controls in the sentiment VARs are jointly insignificant.

view commercial real estate and the general stock market as distinct markets. In the INDRES and ΔINDRES equations, I find that lagged stock market sentiment, $INDSMS_{t-1}$, does not explain the variation in real estate sentiment, regardless of whether sentiment is specified in levels or changes (columns 5 and 7). Similarly, I find no role for INDRES in explaining the variation in INDSMS over time. These results provide additional evidence that commercial real estate is an asset class separate and distinct from the general stock market.

Dynamic Relations between Returns and Sentiment

Table 2-6 and Table 2-7 contain results from the estimation of unrestricted VAR models with both real estate returns and changes in sentiment specified as endogenous variables. While the use of levels may capture the impact of sentiment conditional on the current state of investor beliefs, investors are more likely to be concerned with changes in sentiment as asset prices reflect updates in investor expectations. For example, if investor sentiment decreases, even if the current sentiment level is high, investors may interpret this as negative information (Brown and Cliff, 2004). Although not separately tabulated, specifications utilizing the level of sentiment produce similar results.

Table 2-6, reports results from the joint estimation of public REIT returns (REITRET) and changes in the two measures of investor sentiment in the commercial real estate market; Table 2-7 contains the corresponding results from the joint VAR estimation of private NPI returns (NPIRET) and changes in investor sentiment. I first report results from the estimation of VAR models that include the following exogenous control variables: TBILL, TERMSP, DEFAULTSP, INFL, MKT, SMB, HML, and UMD. In examining aggregate return predictability, Baker and Wurgler (2007) show that in periods where sentiment is more than one standard deviation above its average, subsequent equity returns are, on average, lower. To isolate high sentiment periods, I also report specifications that include a sentiment indicator variable for

periods in which sentiment is more than one standard deviation above its average, SENT-HIGH$_{t-1}$.

Turning first to results using INDRES without the high sentiment indicator variable (Table 2-6, column 1), I find that current quarter REIT returns are positively influenced by REIT returns in quarter t-2, but not by returns in quarter t-1. The estimated coefficient on both ΔSENT$_{t-1}$ and ΔSENT$_{t-2}$ cannot be distinguished from zero. However, with the addition of the high sentiment dummy variable (column 3), the estimated coefficient on ΔSENT$_{t-1}$ is positive and statistically significant. Moreover, the coefficient on SENT_HIGH$_{t-1}$ is negative (-0.028) and significant (p-value=0.010), suggesting that when sentiment is high, subsequent REIT returns are on average lower, consistent with Baker and Wurgler (2007).

If DRES is used in place of INDRES (columns 5 through 8), prior REIT returns continue to predict current REIT returns with a two quarter lag. Moreover, changes in DRES over the prior quarter are positively associated with REIT returns in the current quarter. The addition of a high sentiment indicator variable (column 7) slightly increases the magnitude and significance of the coefficient on ΔSENT$_{t-1}$. The estimated coefficient on SENT_HIGH$_{t-1}$ is again negative, but cannot be distinguished from zero in this specification. Overall, the results in Table 2-6 provide support for the hypothesis that quarterly REIT returns are driven, in part, by changes in investor sentiment over the prior quarter.

Turning to the ΔSENT equations estimated jointly with the REITRET equations. As can be seen in column 2 of Table 2-6, changes in INDRES display no relation to lagged REIT returns. Thus, although sentiment appears to predict REIT returns with a one quarter lag, prior REIT returns do not predict investor sentiment. This absence of a feedback loop between returns and sentiment is also found when DRES is used in place of INDRES (columns 6 and 8). The

estimated coefficients on both $\Delta SENT_{t-1}$ and $\Delta SENT_{t-2}$ in the $\Delta SENT$ equation, when utilizing INDRES (columns 2 and 4), are negative and significant, indicating that increases in sentiment predict decreases in subsequent quarters. This result is consistent with the negative serial correlation of INDRES reported in Table 2-2. If $SENT\_HIGH_{t-1}$ is included in the specification (column 4), the estimated coefficient on $\Delta SENT_{t-1}$ remains negative and significant. Moreover, the estimated coefficient on $SENT\_HIGH_{t-1}$ is negative and significant (p-value=0.028). Thus, both average REIT returns and changes in sentiment are smaller in magnitude following periods of high sentiment. The VAR results obtained using REIT returns and DRES (columns 5 through 8) are very similar to those obtained from the joint REITRET and INDRES estimations. That is, increases in DRES predict significant decreases in DRES in the following quarter. Moreover, changes in investor sentiment are related to the level of sentiment in the prior quarter.

Table 2-7 contains VAR results from the joint estimation of private real estate returns (NPIRET) and changes in investor sentiment. When using INDRES (columns 1 through 4), the estimated coefficients on both $NPIRET_{t-1}$ and $NPIRET_{t-2}$ are positive and highly significant. This result is expected given the previously discussed autocorrelation in the NPI return series.

Controlling for the smoothed nature of NPI returns with lagged NPI returns, the estimated coefficient on $\Delta SENT_{t-1}$ is positive and significant. The magnitude of this short-run effect is approximately half as large as the corresponding short-run public market sentiment effect observed in Table 2-6. Similar to the public market results, the addition of a high sentiment indicator variable (column 3 of Table 2-7) increases the estimated magnitude and significance of $\Delta SENT_{t-1}$. Nevertheless, the coefficient on $\Delta SENT_{t-1}$ remains half as large as its magnitude in the public real estate market. Thus, although limits to arbitrage in private markets are substantial, the short-run price impact of sentiment is smaller than the impact in public markets. This result

reflects, in part, the short-run dominance of institutional investors within the private real estate market. The estimated coefficient on $SENT\_HIGH_{t-1}$ is negative (-0.009) and significant (p-value=0.074). This suggests that, similar to public market returns, private market returns are lower, on average, when sentiment is extremely high in the prior quarter.

When DRES is used in place of INDRES (columns 5 through 8), changes in DRES over the prior quarter are positively associated with returns in the current quarter (p-value=0.009). The addition of $SENT\_HIGH_{t-1}$ to the specification (column 7) marginally increases the magnitude and significance of the coefficient on $\Delta SENT_{t-1}$. However, similar to the public market results, the estimated coefficient on $SENT\_HIGH_{t-1}$ cannot be distinguished from zero. In summary, the results in Table 2-7 provide strong support for the hypothesis that changes in investor sentiment are predictive of private market real estate returns in the subsequent quarter.

Finally, turning to the ΔSENT equations estimated jointly with the NPIRET equations, inspection of column 2 in Table 2-7 reveals that the estimated coefficient on both $\Delta SENT_{t-1}$ and $\Delta SENT_{t-2}$ are negative and significant, indicating that increases in indirect sentiment predict decreases in sentiment in subsequent quarters. However, in contrast to the public market results, changes in INDRES are negatively and significantly related to lagged NPI returns. That is, higher NPI returns in quarter t-1 predict smaller changes in sentiment in quarter t. This result also holds in the presence of a high sentiment dummy (column 4). When using NPI returns and DRES as the endogenous variables in the VAR specification (columns 6 and 8), I find that increases in DRES predict significant decreases in DRES in the following quarter. Moreover, changes in sentiment are associated with the level of sentiment in the prior quarter (column 8). However, changes in DRES are not related to lagged NPI returns.

Taken together, the results reported in Tables 2-6 and 2-7 strongly suggest that changes in investor sentiment are predictive of returns in the following quarter in both public and private commercial real estate markets. The public market results, however, are in contrast to Brown and Cliff (2004) who find no evidence that sentiment predicts subsequent short-run returns in public equity markets. Moreover, the magnitude of the short-run effect of sentiment on returns is greater in public markets than in private markets, particularly when using the direct measure of investor sentiment. In public markets, I find no evidence that past returns predict changes in sentiment. Interestingly, in private markets I do find some evidence of a feedback loop between returns and indirect sentiment.

As a robustness check, I also use the Transaction Based NCREIF Index (TBI) in place of the NPI. The TBI is a statistical index of price appreciation and total returns constructed using only those properties in the NCREIF database that sold during the quarter. Thus, the TBI is constructed to avoid the potential smoothing problem associated with the NPI. Though not tabulated, the use of the TBI index in place of the NPI strengthens the magnitude and significance of the sentiment coefficients using both DRES and INDRES, particularly when sentiment is measured in levels.

Further evidence on the impact of sentiment on public and private market real estate returns is provided by the VAR generalized impulse response functions displayed in Figure 2-3. Panels A and B depict the response of quarterly REIT returns to a one standard deviation change in indirect (Panel A) and direct real estate sentiment (Panel B). The middle curve in each figure represents the estimated diffusion of quarterly REIT returns to the shock in sentiment. The remaining two curves represent the 95% confidence interval around the estimated response.

Panels A and B of Figure 2-3 reveal an initial increase in REIT returns in response to a shock in investor sentiment, which quickly dissipates over subsequent quarters.

Panels C and D display the response of NPI returns to a one standard deviation change in indirect and direct real estate sentiment, respectively. In contrast to the REIT results, the response of private market returns to an innovation in sentiment appears to persist over subsequent quarters. In addition, the magnitude of the initial increase in returns is noticeably smaller than what is observed in the public market results, consistent with private market investors being better informed and more sophisticated. The long-run impacts of sentiment on returns are addressed in detail in the subsequent long-horizon regression analysis.

Stock Market Sentiment Effects

As displayed in Table 2-3, the indirect measure of general stock market sentiment is negatively correlated with the indirect measure of real estate sentiment ($\rho = -0.194$) and displays limited correlation with the direct measure of real estate sentiment ($\rho = 0.275$). These low correlations suggest commercial real estate is often viewed by investors as an asset class separate and distinct from the general stock market.

To further test this hypothesis, I estimate a set of VAR models in which real estate returns, real estate sentiment, and stock market sentiment are treated as endogenous variables in a three equation VAR model. In addition to the three endogenous variables, I retain the full set of exogenous control variables used previously. Although not reported, the inclusion of general stock market sentiment does not affect my real estate VAR results. Private market real estate returns remain positively and significantly related to lagged real estate sentiment, both indirect and direct. In addition, the relation between lagged real estate sentiment and public market real estate returns is consistent with prior results. It is important to reiterate that real estate sentiment

and stock market sentiment are not predictive of each other. These results are virtually unchanged if direct real estate sentiment is used in place of indirect real estate sentiment.

Long-Horizon Regression Results

Long-Run Relation between Returns and Sentiment

Shleifer and Vishny (1997) theorize that investor sentiment may have a more prolonged impact on pricing in markets with considerable limits to arbitrage, such as private markets. As the impact of sentiment on pricing deepens, precisely the time when returns to arbitrage would be the greatest, informed investors are unable to take immediate advantage of the mispricing. Consequently, prices may continue to move further away from fundamental values. In the longer-run, however, sentiment should eventually be negatively related to subsequent long-horizon returns as price reversion occurs. In highly segmented and illiquid private markets, however, it is also more difficult for participants to determine property values. The lack of transactions may cause the effects of sentiment to be revealed more slowly and to be more persistent. Therefore, a positive relation between sentiment and returns may alternatively exist in the longer run as prices are slower to revert to fundamental value. By examining the empirical relation between investor sentiment and long-horizon returns in two markets that share similar underlying assets, I am able to shed additional light on the differential effect of investor sentiment on asset pricing in both public and private markets.

Table 2-8 reports bias-adjusted coefficient estimates and bootstrapped p-values for long-horizon regressions corresponding to the specification in Equation 2-2.[18] In the long-run regressions, sentiment is expressed in levels as I am interested in depicting longer-term patterns in subsequent returns conditional on the state of sentiment in prior periods. Focusing first on the

[18] The reported results are robust to the inclusion of additional exogenous controls, including lagged returns, liquidity, and dividend yields.

REITRET regressions using the indirect sentiment measure (column 1), the estimated coefficient on INDRES is negative and significant across the one-, two-, three-, and four-year horizons. The magnitude and significance of the estimated coefficients also decrease as the return horizon increases beyond the second year. These results, in conjunction with the short-run indirect sentiment results in Table 2-6, are consistent with predictions from the theoretical literature in which the initial sentiment-induced mispricing is subsequently reversed in the long-run. Recall, in periods of extremely high-sentiment, the reversal begins in the subsequent period when using INDRES, as reported in Table 2-6. However, in the long-horizon REITRET regressions that make use of the direct sentiment measure (column 2 of Table 2-8), there is a one-year continuation in returns following periods of sentiment-induced mispricing. This result is again consistent with the short-run direct sentiment results reported in Table 2-6, where there is a positive short-run sentiment impact and no significant high sentiment period reversal. However, the positive relation between long-horizon REIT returns and DRES is reversed after one year as the coefficient estimate on DRES for a two-year horizon cannot be distinguished from zero. Furthermore, the estimated coefficient on DRES is negative and significant for both the three- and four-year return horizons. Thus, the price reversal after the first year is substantial enough to turn the relation between sentiment and REIT returns negative for longer holding periods.

The long-horizon NPIRET regression results using indirect and direct sentiment are reported in columns 3 and 4 of Table 2-8. Consistent with Shleifer and Vishny's (1997) theory of limits to arbitrage and the hypothesis that private markets suffer from more limited price revelation in the long-run, private real estate markets appear to be more susceptible to prolonged periods of sentiment-induced mispricing.[19] The results in Table 2-8 document a positive and

[19] There is also a branch of literature theorizing that delays in information transmission among investors may cause prices to move away from intrinsic value. Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that overreaction

statistically significant relation between investor sentiment and long-horizon NPI returns using both measures of sentiment. That is, following periods of high (low) sentiment, private market returns increase (decrease). These sentiment effects on returns are consistent with the previous short-run results (Table 2-7) where I also observe a consistently positive relation between sentiment and subsequent private market returns, although there is a marginally significant short-run reversal effect in periods of very high sentiment when using the indirect sentiment measure. Due to limits to arbitrage, the sentiment induced price changes are not reversed significantly enough in subsequent years to drive sentiment's relation with long-horizon returns negative, though the coefficient estimates on sentiment do decrease in magnitude as the return horizon increases. However, if I estimate the marginal sentiment effect per year, I find that it is insignificant in years two through four and becomes significantly negative in year five. Overall, the long-horizon results strongly suggest that sentiment-induced pricing bubbles in private real estate markets are slow to develop. Moreover, during this particular sample period, they deflate slowly rather than bursting.

The long-horizon private market results are consistent with Lamont and Thaler (2003b) and Scheinkman and Xiong (2003) who argue that short sales restrictions can make arbitrage costly and lead to discrepancies in prices of economically equivalent assets. These results are also consistent with Froot and Dabora (1999) who report differences between the prices of pairs of large companies ("Siamese twins") that trade around the world but have different trading and ownership habitats. They surmise that among other factors, country-specific sentiment shocks might affect relative prices. Of course, an alternative explanation for the positive long-horizon

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to private information and underreaction to public information by informed investors tend to produce short-term continuation of investment returns, but long-term reversals as public information is eventually incorporated into asset prices. Thus, investor sentiment may cause prices to diverge significantly from fundamental values before a reversion ultimately occurs, particularly when there are significant limits to arbitrage.

returns I find is that commercial real estate assets were consistently under priced at acquisition during our sample period. However, given that REITs were also purchasing and selling their assets in the same private market, this explanation does not seem plausible.

Table 2-9 reports the economic magnitude of a one standard deviation increase in sentiment on returns over the indicated horizon. Following Brown and Cliff (2005), I take the bias-adjusted coefficient estimates reported in Table 2-8 and multiply by the number of quarters in the specified return horizon and the standard deviation of the appropriate sentiment variable. Focusing first on the public market results, a one standard deviation increase in INDRES is associated with a 2.9% decrease in returns over the subsequent one year period. The longer-horizon economic impact reaches a negative trough of 11.1% at the two-year return horizon and then rises thereafter. Using DRES and REITRET (column 2 of Table 2-9), a one standard deviation increase in DRES is associated with a 3.8% increase in returns over the subsequent one year period. This continuation of returns is subsequently reversed at longer horizons as a one standard deviation shock to sentiment is associated with a reduction in returns of 3.6, 9.7, and 12.3% over the two, three, and four year horizons respectively. This increasing negative impact is consistent with the market offsetting both a large contemporaneous sentiment effect as well as any continuation of returns that persists into the subsequent quarter(s).

In the private real estate market, a one standard deviation increase in INDRES is associated with a 3.9% increase in returns over the next year. Using DRES, the magnitude of the initial increase in returns following a standard deviation shock to sentiment is slightly larger than is the case when using INRES. Over the subsequent one year period, returns increase 5.5%. Over longer horizons, returns continue to increase, although the marginal change in returns decreases over time. These results are consistent with limits to arbitrage fostering persistence in

sentiment-induced mispricing in private real estate markets and provide evidence in regards to the relative importance of price revelation and limits to arbitrage in the long-run effect of investor sentiment on asset prices. While private markets may have more well-informed institutional investors, significant limits to arbitrage prevent these investors from taking swift action against short-run asset mispricing.

In summary, the impact of investor sentiment on similar underlying assets depends in part on whether the investments are owned and managed in private or public markets. In both markets, excessive optimism (pessimism) drives prices above (below) fundamental value in the short-run. However, the speed of price revelation and the degree to which investors face restrictions in capitalizing on asset mispricing, play important roles in determining the time it takes for prices to revert to intrinsic values over the long-run. In public real estate markets, periods of sentiment-induced mispricing are followed by quicker price reversals. In private real estate markets, on the other hand, the initial sentiment-induced price response is more persistent as the impact of investor sentiment slowly dissipates over time.

Long-Run Stock Market Sentiment Effects

As discussed previously in the VAR analysis, I find that the inclusion of stock market sentiment does not affect the short-run results. To examine if stock market sentiment impacts real estate returns in the long-run, I implement long-horizon regressions that include the indirect real estate sentiment measure, INDRES, as well as the indirect measure of general stock market sentiment, INDSMS.I retain the full set of exogenous control variables used previously. Although not tabulated, the inclusion of stock market sentiment does not affect the long-run results. Coefficient estimates and statistical significance of the real estate sentiment variable are virtually unchanged from the results reported in Table 2-8, while the long-run impact of stock market sentiment on real estate returns is not statistically different from zero.

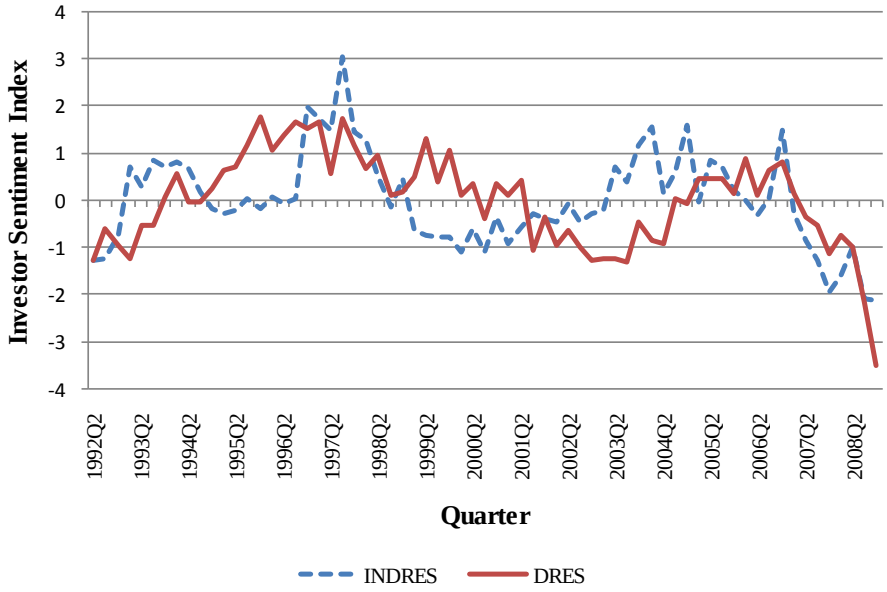
Summary and Conclusion

Sentiment is the component of investor expectations not based on a careful and complete analysis of market fundamentals. With the emergence of the "noise trader" and limits to arbitrage theories of De Long et al. (1990) and Shleifer and Vishny (1997), a growing empirical literature has begun to focus on measuring and quantifying the effects of investor sentiment on asset pricing. Although results vary, a number of recent articles document a significant role for sentiment in the valuation of assets in public stock markets.

The focus on public markets in the existing literature is understandable given the difficulties associated with obtaining return information on investments that trade in private markets. Nevertheless, private investment markets are large in size and provide an appealing testing ground for examining sentiment's pricing role. Relative to more liquid public markets, private investment markets exhibit significant information asymmetries and illiquidity. Moreover, the inability to short-sell in private markets impedes the opportunity for informed arbitrageurs to counteract mispricing.

I posit that investor sentiment plays a more persistent role in pushing asset prices away from their fundamental values in private markets because of increased illiquidity and limits to arbitrage. No previous research, however, has directly investigated the relative importance of sentiment in public and private asset markets. This paper provides a contribution to the investor sentiment literature by examining the short- and long-run relation between sentiment and the pricing of similar underlying assets that are owned and traded in two distinct investment environments. In addition, this study provides evidence of the relative importance of sentiment-driven investor demand and limits to arbitrage in asset mispricing within both the short- and long-run.

Using vector autoregressive (VAR) models, I find evidence of a positive relation between investor sentiment and subsequent quarter returns in both public and private real estate markets. The magnitude of this short-run effect is larger in the public real estate market, which is consistent with private market investors being better informed and more sophisticated. Using long horizon regressions, I also provide evidence that periods of sentiment-induced mispricing are followed by quicker price reversals in public real estate markets. In contrast, private real estate markets are more susceptible to prolonged periods of sentiment-induced mispricing. These results support the hypothesis that limits to arbitrage and delays in price revelation play important roles in determining the time it takes for prices to revert to fundamental values.



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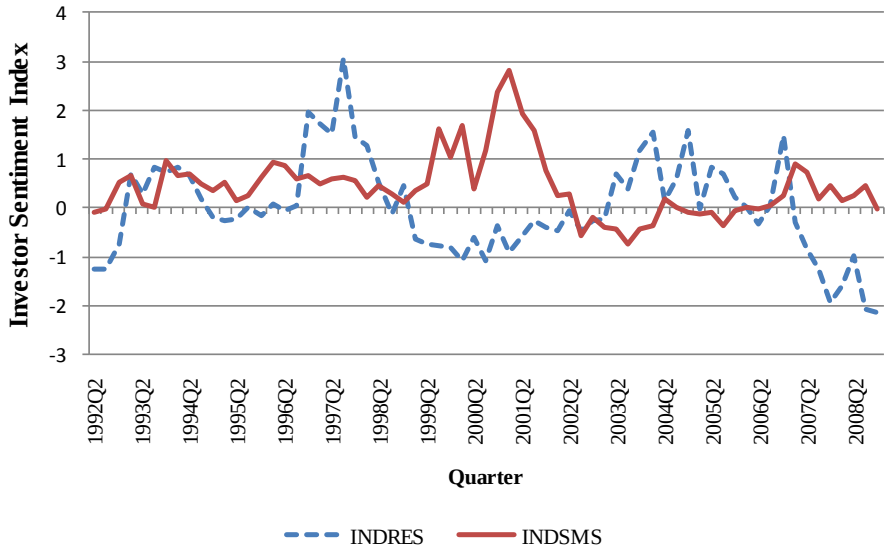


B

Figure 2-1. Investor sentiment indices. A) This figure plots levels of direct (DRES) and indirect (INDRES) investor sentiment indices for the commercial real estate market from 1992:Q2 to 2008:Q4. B) This figure plots levels of indirect investor sentiment indices for the commercial real estate market (INDRES) and the general stock market (INDSMS) from1992:Q2 to 2008:Q4.

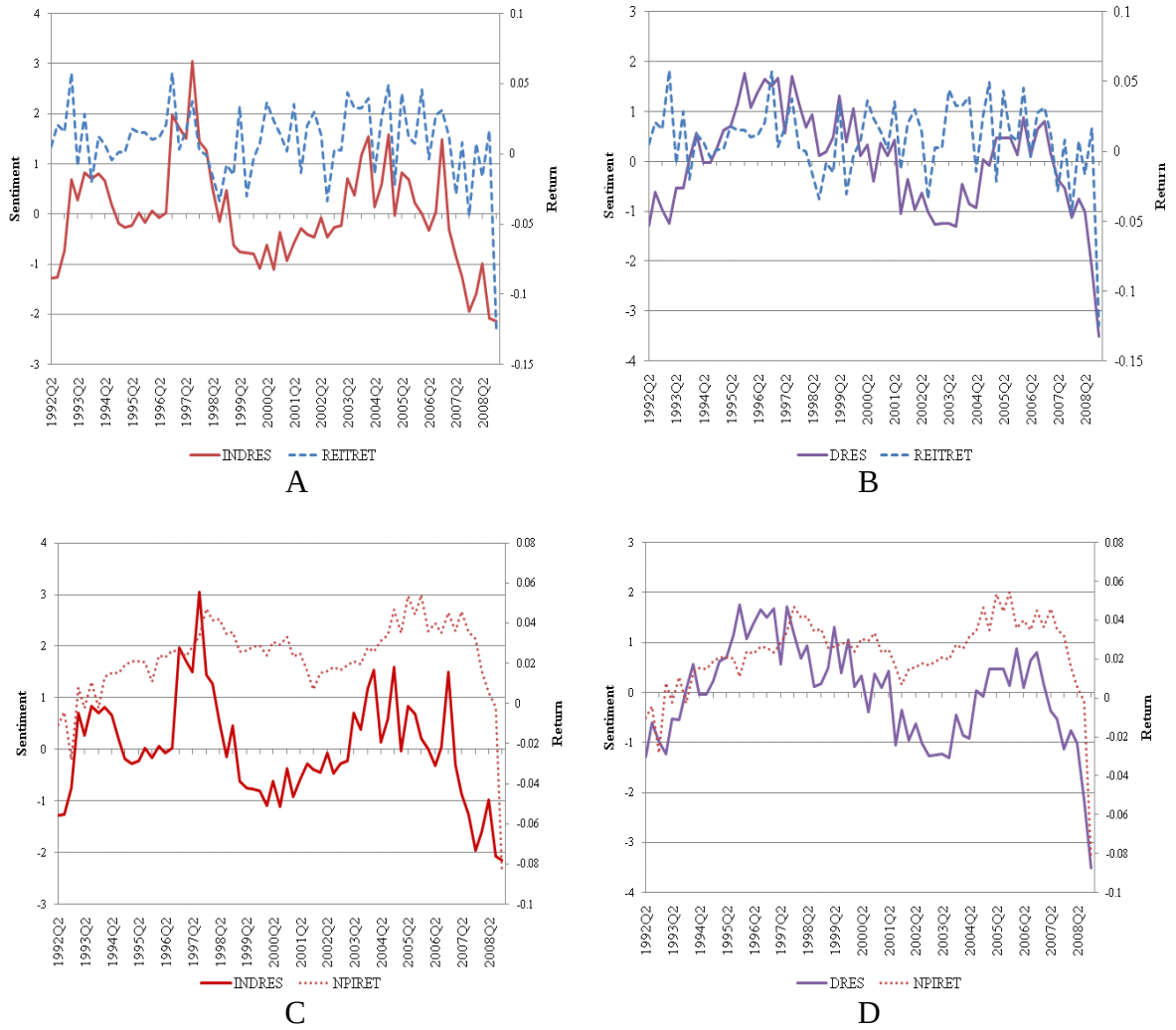


Figure 2-2. Investor sentiment and returns. A) This figure plots levels of the indirect (INDRES) investor sentiment index for the commercial real estate market and the aggregate return index for publicly traded REITs (REITRET) from 1992:Q2 to 2008:Q4. B) This figure plots levels of the direct (DRES) investor sentiment index for the commercial real estate market and the aggregate return index for publicly traded REITs (REITRET) from 1992:Q2 to 2008:Q4. C) This figure plots levels of the indirect (INDRES) investor sentiment index for the commercial real estate market and the aggregate return index for the private commercial real estate market (NPIRET) from 1992:Q2 to 2008:Q4. D) This figure plots levels of the direct (DRES) investor sentiment index for the commercial real estate market and the aggregate return index for the private commercial real estate market (NPIRET) from 1992:Q2 to 2008:Q4.

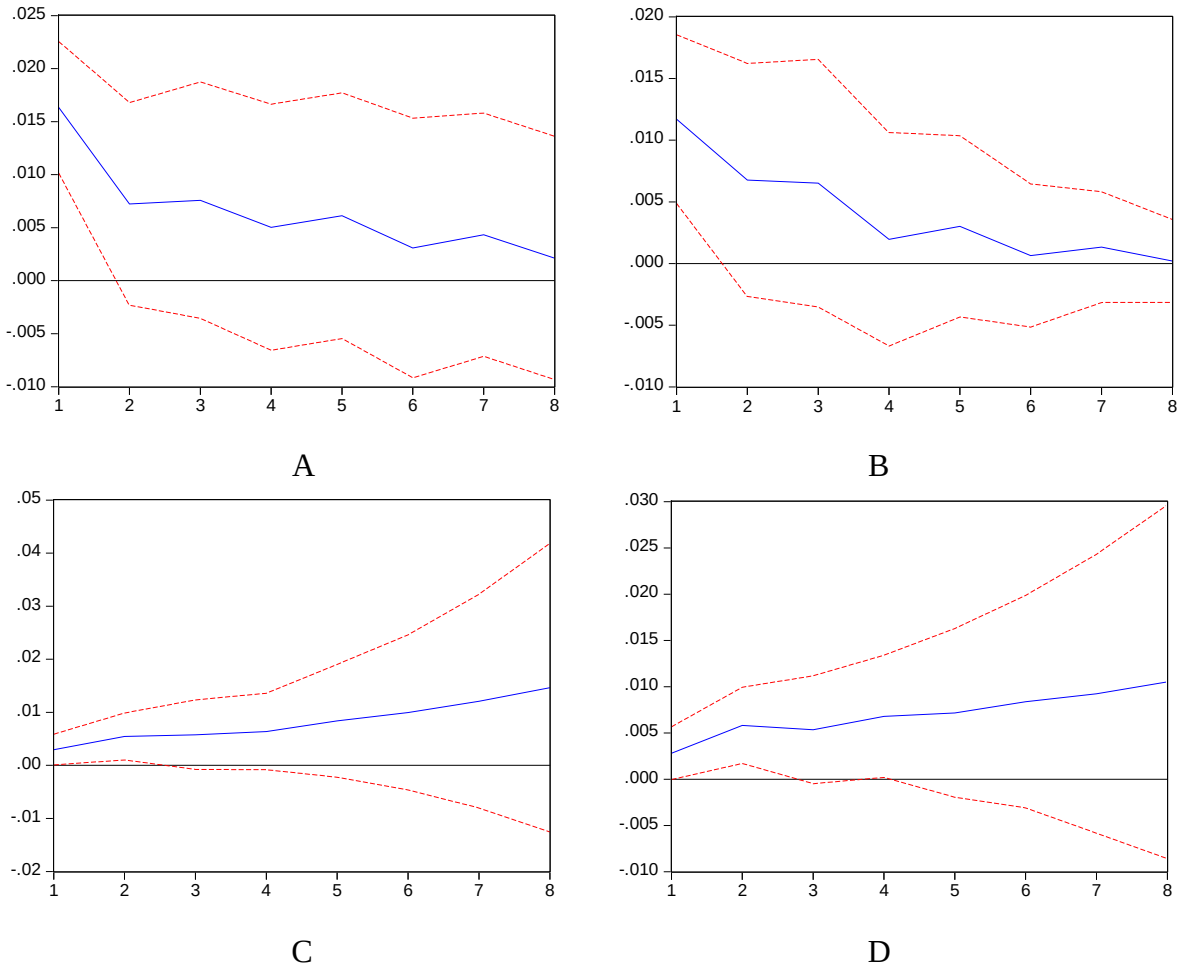


Figure 2-3. Impulse response functions: investor sentiment and returns. This figure represents the generalized impulse response functions corresponding to estimated VAR models from Table 2-6 and Table 2-7 with sentiment measured in changes and including the high sentiment indicator. A) This figure depicts the percentage response in the aggregate return index for publicly traded REITs (REITRET) to a one standard deviation change in the indirect (INDRES) investor sentiment index for the commercial real estate market. B) This figure depicts the percentage response in the aggregate return index for publicly traded REITs (REITRET) to a one standard deviation change in the direct (DRES) investor sentiment index for the commercial real estate market. C) This figure depicts the percentage response in the aggregate return index for private commercial real estate (NPIRET) to a one standard deviation change in the indirect (INDRES) investor sentiment index for the commercial real estate market. This figure depicts the percentage response in the aggregate return index for private commercial real estate (NPIRET) to a one standard deviation change in the direct (DRES) investor sentiment index for the commercial real estate market.

Table 2-1. Descriptive statistics: sentiment proxies.

	Sentiment Proxy	Mean	Median	St. Dev	Min	Max	Serial Correlation Levels	Serial Correlation Changes
INDRES	REIT NAV Premium	0.033	0.031	0.115	-0.244	0.302	0.81***	-0.31**
	Percentage of Properties Sold	0.022	0.023	0.013	0.002	0.057	0.60***	-0.48***
	Number of REIT IPOs	2.493	1.000	4.069	0.000	20.000	0.83***	0.06
	Avg. First-Day Ret. REIT IPO	0.039	0.025	0.052	-0.025	0.268	0.06	-0.58***
	Share of REIT Equity Issues	0.221	0.234	0.411	-2.044	1.674	-0.34***	-0.77***
	Commercial Mortgage Flows	0.002	0.004	0.011	-0.029	0.024	0.60***	-0.41***
	REIT Mutual Fund Flows	0.304	0.160	1.295	-4.513	3.605	0.40***	-0.11
DRES	Apartment	6.300	6.400	0.700	3.900	7.600	0.61***	-0.38***
	Industrial R&D	5.100	5.100	0.800	3.000	6.700	0.80***	-0.30**
	Industrial Warehouse	6.300	6.300	0.600	4.500	7.700	0.72***	-0.40***
	CBD Office	5.500	5.700	1.100	2.800	7.300	0.88***	-0.19
	Suburban Office	5.300	5.300	1.200	2.800	7.500	0.92***	-0.20
	Neighborhood Retail	5.900	6.000	0.700	3.400	7.200	0.60***	-0.38***
	Power Center	5.000	5.000	1.100	2.700	6.800	0.85***	-0.38***
	Regional Malls	5.400	5.400	0.800	2.900	6.700	0.59***	-0.44***
INDSMS	Closed-end Fund Discount	0.071	0.067	0.036	-0.013	0.191	0.92***	-0.19
	NYSE Share Turnover	0.136	0.136	0.129	-0.249	0.543	0.33***	-0.51***
	Number of IPOs	29.42	23.00	23.10	0.000	106.0	0.80***	-0.27***
	Avg. First Day Ret. IPOs	0.193	0.140	0.212	-0.199	1.162	0.76***	-0.44***
	Share of Equity Issues	0.118	0.102	0.073	0.015	0.539	0.61***	-0.33***
	Dividend Premium	-0.147	-0.137	0.122	-0.602	0.128	0.92***	0.06

This table reports descriptive statistics for each component of the indirect real estate sentiment index (INDRES), the direct real estate sentiment index (DRES), and the indirect stock market sentiment index (INDSMS). Mean, median, standard deviation, minimum, maximum, and serial correlation of levels and changes are reported. Descriptive statistics are reported in decimal form. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-2. Descriptive statistics: aggregate sentiment measures.

						Serial Correlation	
Sentiment Measure	Mean	Median	St Dev	Min	Max	Levels	Changes
INDRES	0.000	-0.070	1.000	-2.146	3.051	0.73***	-0.29**
DRES	0.000	0.117	1.000	-3.508	1.762	0.81***	-0.35***
INDSMS	0.426	0.343	0.651	-0.758	2.799	0.76***	-0.14

This table reports descriptive statistics for each aggregate sentiment index: the indirect real estate sentiment index (INDRES), the direct real estate sentiment index (DRES), and the indirect stock market sentiment index (INDSMS). Mean, median, standard deviation, minimum, maximum, and serial correlation of levels and changes are reported. INDRES is the first principal component extracted from seven underlying proxies of investor sentiment in commercial real estate markets: i) the REIT price premium to net asset value, (ii) the percentage of properties sold from the NCREIF Property Index, (iii) the number of REIT IPOs, (iv) the average first-day returns on REIT IPOs, (v) the share of net REIT equity issues in total net REIT equity and debt issues, (vi) commercial mortgage flows as a percentage of GDP, and (vii) capital flows to dedicated REIT mutual funds. DRES is the first principal component extracted from investment condition survey responses pertaining to eight property types that are published quarterly by the Real Estate Research Corporation (RERC) in their Real Estate Report. INDSMS is the first principal component extracted from six underlying proxies of investor sentiment in the stock market: (i) the average difference between the net asset values of closed-end fund stock shares and their market prices, (ii) share turnover on the NYSE, (iii) the number of IPOs, (iv) the average first-day returns on IPOs, (v) the share of equity issues in total equity and debt issues, and (vi) the dividend premium. Each index is standardized to have a mean of zero and unit variance for the period over which it was generated. Descriptive statistics are reported in decimal form. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-3. Descriptive statistics and correlations: aggregate sentiment measures.

Sentiment Measure	INDRES	DRES	INDSMS
INDRES	1.000		
DRES	0.478***	1.000	
INDSMS	-0.194	0.275***	1.000

This table reports correlations between each aggregate sentiment index: the indirect real estate sentiment index (INDRES), the direct real estate sentiment index (DRES), and the indirect stock market sentiment index (INDSMS). INDRES is the first principal component extracted from seven underlying proxies of investor sentiment in commercial real estate markets: i) the REIT price premium to net asset value, (ii) the percentage of properties sold from the NCREIF Property Index, (iii) the number of REIT IPOs, (iv) the average first-day returns on REIT IPOs, (v) the share of net REIT equity issues in total net REIT equity and debt issues, (vi) commercial mortgage flows as a percentage of GDP, and (vii) capital flows to dedicated REIT mutual funds. DRES is the first principal component extracted from investment condition survey responses pertaining to eight property types that are published quarterly by the Real Estate Research Corporation (RERC) in their Real Estate Report. INDSMS is the first principal component extracted from six underlying proxies of investor sentiment in the stock market: (i) the average difference between the net asset values of closed-end fund stock shares and their market prices, (ii) share turnover on the NYSE, (iii) the number of IPOs, (iv) the average first-day returns on IPOs, (v) the share of equity issues in total equity and debt issues, and (vi) the dividend premium. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-4. Descriptive statistics: return series and control variables.

Variable	Mean	Median	Std Dev	Min	Max	Serial Correlation
REITRET	0.009	0.012	0.028	-0.125	0.058	-0.04
NPIRET	0.023	0.025	0.020	-0.083	0.054	0.72***
TBILL	0.038	0.044	0.016	0.003	0.062	0.96***
TERMSP	0.016	0.015	0.012	-0.006	0.036	0.93***
DEFAULTSP	0.009	0.008	0.003	0.006	0.030	0.83***
INFLA	0.006	0.006	0.009	-0.039	0.025	-0.13
MKT	0.004	0.012	0.082	-0.223	0.196	-0.01
SMB	0.007	0.002	0.055	-0.108	0.191	0.01
HML	0.004	0.004	0.077	-0.320	0.206	0.16
UMD	0.027	0.019	0.080	-0.201	0.260	-0.07

This table reports descriptive statistics for two quarterly return series, as well as macroeconomic/risk control variables. REITRET measures returns in public commercial real estate markets and is obtained from the CRSP/ZIMAN database. It is the quarterly value-weighted aggregate return index for U.S. equity REITs. NPIRET measures returns in private commercial real estate markets and is provided by the National Council of Real Estate Investment Fiduciaries (NCREIF). It is a quarterly index tracking the total return performance of a large pool of individual commercial real estate properties acquired in the private market for investment purposes only. Macroeconomic/risk control variables include the annualized yield on three-month U.S. Treasury securities (TBILL), the annual slope of the Treasury term structure of interest rates (TERMSP), the annual spread between yields on BAA rated and AAA rated corporate bonds (DEFAULTSP), quarterly inflation (INFLA), as well as the three Fama-French risk factors: MKT, SMB, and HML augmented by a return momentum factor, UMD. Mean, median, standard deviation, minimum, maximum, and serial correlation are reported. Descriptive statistics are reported in decimal form. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-5. Dynamic relations amongst sentiment measures.

	Direct and Indirect Real Estate Sentiment				Indirect Real Estate and Stock Market Sentiment			
	Sentiment in Levels		Sentiment in Changes		Sentiment in Levels		Sentiment in Changes	
End. Variables	INDRES	DRES	ΔINDRES	ΔDRES	INDRES	INDSMS	ΔINDRES	ΔINDSMS
Constant	0.447	1.098	-1.507	0.957	0.722	0.010	-1.252	-0.149
	(0.654)	(0.185)	(0.129)	(0.217)	(0.468)	(0.986)	(0.203)	(0.815)
$DRES_{t-1}$	0.245	0.447***	0.099	-0.420***	-	-	-	-
	(0.148)	(0.001)	(0.567)	(0.002)	-	-	-	-
$DRES_{t-2}$	0.197	0.303**	0.143	-0.010	-	-	-	-
	(0.246)	(0.032)	(0.416)	(0.945)	-	-	-	-
$INDRES_{t-1}$	0.372***	0.058	-0.407***	-0.006	0.625***	-0.080	-0.293**	0.045
	(0.010)	(0.626)	(0.003)	(0.958)	(0.000)	(0.224)	(0.020)	(0.583)
$INDRES_{t-2}$	0.101	-0.039	-0.240*	-0.087	-	-	-	-
	(0.426)	(0.710)	(0.064)	(0.389)	-	-	-	-
$INDSMS_{t-1}$	-	-	-	-	-0.106	0.543***	0.048	-0.179
	-	-	-	-	(0.554)	(0.000)	(0.799)	(0.144)
Adjusted R^2	0.56	0.70	0.04	0.14	0.53	0.60	0.03	-0.04

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with investor sentiment measures specified as endogenous variables. INDRES is the indirect real estate sentiment index, DRES is the direct real estate sentiment index, and INDSMS is the indirect stock market sentiment index. Bivariate models with exogenous controls are estimated. Exogenous control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSP), the spread between yields on BAA rated and AAA rated corporate bonds (DEFAULTSP), inflation (INFLA), as well as the three Fama-French risk factors: MKT, SMB, and HML augmented by a return momentum factor, UMD. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p. Two lags provide the best fit for comparing real estate sentiment measures, while one lag is deemed appropriate for comparison of real estate and stock market sentiment measures. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-6. Dynamic relations between public market returns and sentiment.

	INDRES (Indirect Sentiment)				DRES (Direct Sentiment)			
End. Variables	REITRET	ΔSENT	REITRET	ΔSENT	REITRET	ΔSENT	REITRET	ΔSENT
Constant	0.024	-1.437	0.049	-0.914	0.012	0.893	0.006	0.685
	(0.537)	(0.147)	(0.211)	(0.353)	(0.772)	(0.251)	(0.875)	(0.369)
$REITRET_{t-1}$	-0.162	5.108	-0.088	6.728	-0.112	-3.145	-0.083	-1.992
	(0.503)	(0.400)	(0.706)	(0.254)	(0.611)	(0.464)	(0.708)	(0.636)
$REITRET_{t-2}$	0.554***	2.530	0.691***	5.512	0.416**	1.038	0.440**	2.015
	(0.010)	(0.638)	(0.001)	(0.304)	(0.020)	(0.766)	(0.014)	(0.556)
$\Delta SENT_{t-1}$	0.009	-0.448***	0.012**	-0.367**	0.013*	-0.392***	0.014**	-0.327**
	(0.155)	(0.004)	(0.039)	(0.017)	(0.072)	(0.004)	(0.047)	(0.016)
$\Delta SENT_{t-2}$	-0.004	-0.270*	-0.002	-0.226	0.008	-0.007	0.009	0.027
	(0.533)	(0.081)	(0.756)	(0.132)	(0.268)	(0.959)	(0.219)	(0.841)
$SENT\_HIGH_{t-1}$	-	-	-0.028***	-0.597**	-	-	-0.009	-0.377**
	-	-	(0.010)	(0.028)	-	-	(0.340)	(0.047)
Adjusted R^2	0.04	0.04	0.11	0.09	0.04	0.14	0.03	0.17

This table presents results obtained from estimating two unrestricted vector autoregressive (VAR) models with investor sentiment and public market return measures specified as endogenous variables. INDRES is the indirect real estate sentiment index and DRES is the direct real estate sentiment index. REITRET measures returns in public commercial real estate markets and is obtained from the CRSP/ZIMAN database. It is the quarterly value-weighted aggregate return index for U.S. equity REITs. Exogenous control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSP), the spread between yields on BAA rated and AAA rated corporate bonds (DEFAULTSP), inflation (INFLA), as well as the three Fama-French risk factors: MKT, SMB, and HML augmented by a return momentum factor, UMD. The high sentiment dummy variable, SENT_HIGH, takes a value of one for periods in which the sentiment measure is greater than one standard deviation above its mean value over the sample period. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p. Two lags provide the best fit for estimation. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-7. Dynamic relations between private market returns and sentiment.

	INDRES (Indirect Sentiment)				DRES (Direct Sentiment)			
End. Variables	NPIRET	ΔSENT	NPIRET	ΔSENT	NPIRET	ΔSENT	NPIRET	ΔSENT
Constant	-0.002	0.063	-0.007	-0.188	-0.004	0.768	-0.006	0.614
	(0.931)	(0.964)	(0.767)	(0.892)	(0.850)	(0.505)	(0.793)	(0.583)
$NPIRET_{t-1}$	0.452**	-24.131**	0.516***	-20.922**	0.512***	4.364	0.520***	5.043
	(0.011)	(0.018)	(0.004)	(0.042)	(0.002)	(0.586)	(0.002)	(0.516)
$NPIRET_{t-2}$	0.811***	10.607	0.895***	14.858	0.678***	-2.312	0.666***	-3.415
	(0.000)	(0.363)	(0.000)	(0.207)	(0.000)	(0.800)	(0.000)	(0.699)
$\Delta SENT_{t-1}$	0.004*	-0.376***	0.006**	-0.283*	0.007***	-0.418***	0.008***	-0.342***
	(0.096)	(0.005)	(0.022)	(0.051)	(0.009)	(0.002)	(0.005)	(0.010)
$\Delta SENT_{t-2}$	0.001	-0.298**	0.003	-0.213	0.003	-0.025	0.003	0.020
	(0.686)	(0.019)	(0.272)	(0.119)	(0.313)	(0.855)	(0.239)	(0.884)
$SENT\_HIGH_{t-1}$	-	-	-0.009*	-0.436	-	-	-0.004	-0.380**
	-	-	(0.074)	(0.123)	-	-	(0.286)	(0.043)
Adjusted R^2	0.60	0.11	0.61	0.12	0.62	0.13	0.62	0.17

This table presents results obtained from estimating two unrestricted vector autoregressive (VAR) models with investor sentiment and private market return measures specified as endogenous variables. INDRES is the indirect real estate sentiment index and DRES is the direct real estate sentiment index. NPIRET measures returns in private commercial real estate markets and is provided by the National Council of Real Estate Investment Fiduciaries (NCREIF). It is a quarterly index tracking the total return performance of a large pool of individual commercial real estate properties acquired in the private market for investment purposes only. Exogenous control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSP), the spread between yields on BAA rated and AAA rated corporate bonds (DEFAULTSP), inflation (INFLA), as well as the three Fama-French risk factors: MKT, SMB, and HML augmented by a return momentum factor, UMD. The high sentiment dummy variable, SENT_HIGH, takes a value of one for periods in which the sentiment measure is greater than one standard deviation above its mean value over the sample period. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p. Two lags provide the best fit for estimation. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-8. Long-horizon regression results: coefficient estimates and statistical significance.

	REITRET		NPIRET	
Return Horizon	INDRES	DRES	INDRES	DRES
One-year	-0.007*	0.010*	0.010***	0.014***
	(0.067)	(0.096)	(0.000)	(0.000)
Two-year	-0.014***	-0.004	0.003**	0.008***
	(0.000)	(0.313)	(0.017)	(0.000)
Three-year	-0.007***	-0.008**	0.004***	0.006***
	(0.002)	(0.026)	(0.001)	(0.000)
Four-year	-0.004**	-0.008**	0.003***	0.005***
	(0.034)	(0.018)	(0.001)	(0.002)

This table presents results for the long-horizon regressions. The long-horizon regression specification is as follows:

$$(r_{t+1} + \ldots. + r_{t+k})/k = \alpha(k) + \theta(k)\, z_t + \beta(k)\, S_t + \varepsilon_t$$

where $r_{t+1} + \ldots. + r_{t+k}$ are log returns, k is the number of quarters over which the particular horizon spans, α is the intercept term, z_t is the set of control variables, and S_t is a measure of investor sentiment in commercial real estate. INDRES is the indirect real estate sentiment index and DRES is the direct real estate sentiment index. REITRET measures returns in public commercial real estate markets and is obtained from the CRSP/ZIMAN database. It is the quarterly value-weighted aggregate return index for U.S. equity REITs. NPIRET measures returns in private commercial real estate markets and is provided by the National Council of Real Estate Investment Fiduciaries (NCREIF). It is a quarterly index tracking the total return performance of a large pool of individual commercial real estate properties acquired in the private market for investment purposes only. The set of control variables includes the yield on the three-month Treasury bill, the slope of the Treasury term structure of interest rates, the spread between yields on BAA rated and AAA rated corporate bonds, inflation, the three Fama-French risk factors (MKT, SMB, and HML) and a return momentum factor (UMD). Bias-adjusted coefficient estimates and their associated p-values utilize adjustments derived from the bootstrap simulation procedure documented in the Appendix. 10,000 bootstrap simulations were run for each long-horizon return series within each property type. The sample period spans 1992:Q2 to 2008:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 2-9. Economic significance of long-horizon regression results.

	REITRET		NPIRET	
Return Horizon	INDRES	DRES	INDRES	DRES
One-year	-0.029	0.038	0.039	0.055
Two-year	-0.111	-0.036	0.027	0.066
Three-year	-0.087	-0.097	0.042	0.076
Four-year	-0.072	-0.123	0.056	0.075

This table presents results for the economic significance of coefficient estimates from the long-horizon regressions. The long-horizon regression specification is as follows:

$$(r_{t+1} + \ldots. + r_{t+k})/k = \alpha(k) + \theta(k)\, z_t + \beta(k)\, S_t + \varepsilon_t$$

where $r_{t+1} + \ldots. + r_{t+k}$ are log returns, k is the number of quarters over which the particular horizon spans, α is the intercept term, z_t is the set of control variables, and S_t is a measure of investor sentiment in commercial real estate. INDRES is the indirect real estate sentiment index and DRES is the direct real estate sentiment index. REITRET measures returns in public commercial real estate markets and is obtained from the CRSP/ZIMAN database. It is the quarterly value-weighted aggregate return index for U.S. equity REITs. NPIRET measures returns in private commercial real estate markets and is provided by the National Council of Real Estate Investment Fiduciaries (NCREIF). It is a quarterly index tracking the total return performance of a large pool of individual commercial real estate properties acquired in the private market for investment purposes only. The set of control variables includes the yield on the three-month Treasury bill, the slope of the Treasury term structure of interest rates, the spread between yields on BAA rated and AAA rated corporate bonds, inflation, the three Fama-French risk factors (MKT, SMB, and HML) and a return momentum factor (UMD). To calculate the economic magnitude of a one standard deviation shock to sentiment, I take the bias-adjusted coefficient estimates reported in Table 2-8 and multiply by the number of quarters in the specified return horizon and the standard deviation of the appropriate sentiment variable. Results are reported in decimal form. The sample period spans 1992:Q2 to 2008:Q4.

CHAPTER 3
CREDIT AVAILABILITY AND ASSET PRICING SPIRALS IN ILLIQUID MARKETS

When asset prices crashed in the late 1980s, a branch of theoretical literature focusing on credit cycles emerged that explained how shocks to asset prices could be amplified by a bank's willingness or ability to provide credit (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). In response to the latest credit crunch, however, the relation between asset prices, the availability of credit, and market liquidity has garnered increased attention (e.g., Geanakoplos, 2003; Garleanu and Pedersen, 2007; Longstaff and Wang, 2008; Brunnermeier and Pedersen 2009). Moreover, a number of recent empirical papers testing these theories have emerged, including studies examining how changes in credit availability impact bank balance sheets (Adrian and Shin, 2010), hedge fund performance (Dudley and Nimalendran, 2010; Boyson, Stahel, and Stulz, 2010), and market liquidity in the general stock market (Hameed, Wang, and Viswanathan, 2010). Overall, these studies find that credit constraints affect asset values at times when public markets are relatively illiquid or when assets are highly leveraged.

These recent empirical papers focus on brief periods of illiquidity and credit tightening in relatively liquid markets. However, the existing literature does not address the relation between the availability of credit and asset prices in markets that are persistently illiquid and composed of highly leveraged assets, such as the private commercial real estate market. The relative illiquidity and significant use of leverage in this market setting allows one to better isolate and measure the impact of credit availability on asset prices in both periods of credit tightening and easing. Furthermore, no prior research has tested the relative impact of changes in credit availability on assets with claims on similar cash flows that are traded in markets with different liquidity. However, tests using both private and public real estate markets create a clearer picture of the

interaction between credit availability, market liquidity, and asset price movements in markets with significantly different degrees of liquidity.

In this study, I test the relation between changes in credit availability, market liquidity, and asset prices in both private and public commercial real estate markets. I first examine the time-varying relation between changes in credit availability and market liquidity. I simultaneously test the conditional short-run impact of changes in credit availability on asset prices in both private and public markets. I then test whether changes in asset prices reinforce changes in the availability of credit, thereby creating a spiral effect.

The commercial real estate market provides an appealing testing ground for examining the dynamic relation between credit availability, market liquidity, and changes in asset prices. First, the private commercial real estate market is a relatively illiquid market consisting of highly leveraged assets.[1] Therefore, one would expect asset prices in this market to be relatively sensitive to changes in credit availability not only when credit conditions are tightened, but also when lending standards are eased. Second, unlike other private markets, several representative price return indices for private commercial real estate are available, permitting the calculation of time-weighted price returns that can be compared directly to corresponding price changes in public real estate markets. Third, the underlying properties held by the publicly traded real estate firms I analyze are similar to the property holdings of the institutional real estate investors whose private market returns I also track. Controlling for the security characteristic embedded in public real estate market returns, disparities in the impact of credit availability on price changes in private and public real estate markets can be ascribed to differences in the liquidity characteristics of these two markets.

[1] As a conservative estimate of leverage, the American Council of Life Insurers reports that the average loan-to-value ratio on commercial real estate properties was approximately 68% over the period 1992Q2 to 2008Q4.

Using vector autoregressive (VAR) models, I address two questions. First, do changes in credit availability affect asset price returns over and above the impact of other fundamental control variables? When investors find it difficult to obtain credit for acquisitions or refinancing, market liquidity decreases, which, in turn, puts downward pressure on prices. In contrast, when access to credit is eased, an increase in the use of leverage for acquisitions will put upward pressure on asset prices. Therefore, I test whether changes in credit availability, after controlling for the impact of market liquidity, impact asset prices. Second, do price changes affect changes in future credit availability over and above the impact of other fundamental control variables? As prices fall in an illiquid market, the risk of financing an additional transaction rises and credit markets tighten further. On the other hand, as asset prices increase, lenders may further ease credit standards to take advantage of this timely profit opportunity. Consequently, I also test the hypothesis that subsequent price changes will lead to further changes in credit availability for assets that are traded in relatively illiquid markets.

I find that credit availability is a significant determinant of subsequent price movements in both private and public commercial real estate markets. In particular, a tightening (easing) in bank lending standards is negatively (positively) related to subsequent price movements in both the private property and public REIT markets, even after controlling for the impact of market liquidity and other fundamentals. These results suggest that leverage is a key factor in determining credit market effects on pricing. I also find evidence of a spiral effect, in which changes in price movements reinforce future changes in credit availability. However, this spiral effect is concentrated in relatively illiquid segments of the commercial real estate market. In particular, I document a feedback effect of lagged price changes on subsequent credit availability in the private commercial real estate market, the lowest liquidity quartiles of the public

commercial real estate market, and the relatively illiquid market for REIT preferred shares. Consistent with the theoretical predictions of Brunnermeier and Pedersen (2009) and Geanakoplos (2003), these results suggest that while leverage plays a significant role in determining the effects of credit availability on pricing, the underlying liquidity with which assets trade is a key factor in determining the likelihood of a liquidity spiral. In short, a lack of liquidity creates the market setting for a spiral effect.

Anecdotal evidence and recent theoretical work by Shleifer and Vishny (2010) also suggest that investor sentiment plays a role in credit market effects. Therefore, as an additional robustness check I also include a proxy for investor sentiment as a fourth endogenous variable in my VAR specifications. Consistent with Shleifer and Vishny (2010), I find that changes in investor sentiment predict future changes in credit availability. I also find weak evidence of a feedback effect between changes in credit availability and future changes in investor sentiment. These results suggest banks respond to increasing investor sentiment by easing credit standards, thereby making credit more readily available to potential investors when they are most optimistic. However, during a market downturn in which investors are becoming increasingly pessimistic, banks tend to tighten lending standards, which can have a destabilizing effect on asset prices. This raises an interesting policy question pertaining to the extent to which lenders and their regulators have the ability to reduce the probability that an asset pricing bubble emerges by restricting the amount of credit provided during boom periods or ease the severity of a downturn by making credit available when markets are distressed.

Background Literature and Research Development

Recent theoretical work in the asset pricing literature makes an important distinction between two types of liquidity: market liquidity and funding liquidity (Brunnermeier and Pedersen, 2009; Brunnermeier, 2009). Market liquidity refers to the ease with which an investor

can find another party to take the opposite side of a transaction. Funding liquidity refers to the ease with which an investor can obtain capital from a financier. In other words, funding liquidity is the degree to which investors have access to credit. In an efficient market, asset price movements should be invariant to changes in credit availability when markets are relatively liquid. Any deviations in price that result from a temporary credit shock should be quickly arbitraged away (Fama, 1970). However, arbitrageurs may at times face funding constraints and be unable to provide market liquidity when it is needed the most (Shleifer and Vishny, 1997). When funding constraints are so severe that investors can no longer maintain their existing positions, asset values drop significantly and markets become illiquid, as was evident in the Long Term Capital Management (LTCM) crisis of 1998. Recent developments in financial markets further suggest that shocks to market conditions can be severe enough to cause market liquidity to fluctuate significantly over time.

Brunnermeier and Pedersen (2009) establish a theoretical basis for the endogenous variation of market conditions and credit requirements. In particular, they focus on the relation between credit constraints and asset pricing, the amplifying effects of their interaction, and differences in these impacts across high- and low-leverage securities during periods of market illiquidity. When credit availability is tight, traders become reluctant to take on positions, especially ‘capital intensive’ positions in highly leveraged assets. This lack of credit availability lowers market liquidity. Under certain conditions, decreased market liquidity increases the risk of financing an acquisition, thus further tightening the availability of funds for investment. This is what Brunnermeier and Pedersen (2009) refer to as a margin spiral. When credit constraints are tightened in periods of market illiquidity, the effect may be destabilizing and lead to a second type of liquidity spiral that has an amplifying effect on asset prices. If credit constraints continue

to be tightened as asset prices fall, investors may be forced to de-lever their position by selling assets into an illiquid market. In short, declining asset prices and tighter credit constraints may reinforce one another causing a spiral to ensue. Brunnermeier and Pedersen (2009) refer to this as a loss spiral. Therefore, when asset markets are relatively illiquid, prices may be driven more in the short-run by changes in the availability of credit than by movements in fundamentals.

Geanakoplos (2003) presents a similar collateral based theory of such spirals. When investors can readily obtain credit to purchase or refinance an asset, optimistic investors are able to hold a larger fraction of the capital stock. Geanakoplos (2003) calls these optimistic investors "natural buyers." Using large amounts of leverage, these optimistic buyers tend to push up prices to levels that exceed fundamental values. These price increases, in turn, increase the confidence and risk tolerance of lenders, thereby fueling a relaxation of underwriting standards. This increased availability of credit may put additional upward pressure on asset prices, further increasing the confidence of lenders. Said differently, access to leverage is pro-cyclical. However, if a negative credit shock occurs that increases lender uncertainty (for example, the bankruptcy of Lehman Brothers in 2008), lenders may tighten credit standards in response. This tightening in credit markets may, in turn, force highly leveraged optimists to de-lever their current positions and use less leverage on new acquisitions, thereby putting downward pressure on prices. Since it is now harder to borrow money, optimistic buyers are less able to obtain financing for investment. Therefore, asset markets become less liquid and the proportion of "natural buyers" in the market decreases. This decrease in market liquidity puts downward pressure on prices and further increases the risk of providing financing. Therefore, asset prices will be sensitive to changes in the availability of credit in markets in which transactions are highly leveraged.

Previous empirical research has examined the role of market liquidity in asset pricing. Amihud (2002) finds that aggregate market liquidity is an important factor in determining a firm's expected returns. Furthermore, Pastor and Stambaugh (2003) provide evidence that a firm's sensitivity to fluctuations in market liquidity (i.e., its liquidity beta) is a significant state variable in asset pricing. However, few empirical analyses have tested the interaction between market liquidity, credit constraints, and asset prices. Hameed, Kang, and Viswanathan (2010) find that periods of significant negative stock market returns cause market liquidity to decrease, particularly during times in which funding constraints are tight. Dudley and Nimalendran (2010) provide evidence that returns on leveraged hedge funds are highly sensitive to changes in funding risk, especially during periods of market illiquidity. Finally, Adrian and Shin (2010) find that the amount of leverage carried on bank balance sheets is sensitive to asset price movements of the underlying collateral, especially during a financial market downturn.

Overall, the extant theoretical literature predicts that the sensitivity of market liquidity and asset prices to the availability of funds for investment is most pronounced for assets that are relatively illiquid and highly leveraged. However, no research to date has tested the dynamic relation between the availability of credit and asset pricing for highly leveraged assets that trade in relatively illiquid markets. By testing the impact of changes in credit availability on asset prices within the relatively illiquid and highly leveraged private commercial real estate market, this study provides an experimental setting that allows one to better isolate and measure the potential impact of credit market availability on asset prices in both periods of credit easing and tightening, thereby providing a unique contribution to the literature.

I further extend this contribution by measuring the relative impact of credit availability on prices of similar assets traded in markets with different liquidity. Tests using a parallel market

with varying degrees of liquidity create a clearer picture of the interaction between credit availability, liquidity, and asset price movements. Prior empirical research has shown that differences in market liquidity can lead to discrepancies in prices of economically equivalent assets traded in different markets. For example, Froot and Dabora (1999) find that pairs of large companies ("Siamese twins") that trade around the world are priced differently because of differences in trading environments. Similarly, Chan, Hong, and Subrahmanyam (2008) show that market liquidity is an important determinant of the price difference between ADRs (American Depository Receipts) and their underlying shares. However, no prior research has examined the role of credit availability (funding liquidity) within this context. Using relatively liquid REIT common shares, liquidity and leverage sorted REIT portfolios, and the relatively illiquid market for REIT preferred shares, I examine the relative effects of changes in credit availability on the prices of similar assets traded in markets with varying liquidity. This framework also provides an appealing setting to test whether the relative likelihood of a spiral effect is dependent on the underlying liquidity with which these assets trade.

Anecdotal evidence also suggests the expansion of credit availability during the real estate boom of the early-to-mid 2000s was in part driven by the response of creditors to increasing investor optimism and speculative demand for these assets. If banks cater their lending decisions to shifts in investor sentiment (Shleifer and Vishny, 2010), a feedback loop may be created between changes in credit availability and changes in investor sentiment. With the anecdotal evidence and theoretical motivation in mind, I further extend my analysis of credit market effects by including a proxy for investor sentiment as a fourth endogenous variable in the VAR specifications.

Empirical Methodology

Brunnermeier and Pedersen (2009) suggest that liquidity-based price impacts can be tested empirically by examining short-run price changes, whereas the impact of fundamental volatility is more likely to be evident in long-run price movements. To capture the short-term dynamics between credit availability, market liquidity, and asset price changes, I employ vector autoregressive (VAR) models. In its simplest form, a VAR model is composed of a system of regressions where two or more dependent variables are expressed as linear functions of their own and each other's lagged values, as well as other exogenous control variables. In more technical terms, a vector autoregression model is the unconstrained reduced form of a dynamic simultaneous equations model. An unrestricted p^{th}-order Gaussian VAR model can be represented as:

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_k Y_{t-p} + \varepsilon_t \qquad (3\text{-}1)$$

where Y_t is a vector of variables, μ is a p x 1 vector of intercepts, $\Phi_1, \Phi_2, \ldots, \Phi_k$ are p x p matrices of parameters with all eigenvalues of Φ having moduli less than one so that the VAR is stationary, and e_t is a vector of uncorrelated structural shocks [~ NID(0,Ω)]. I obtain maximum likelihood estimates of Φ and Ω using iterated least squares. The number of quarterly lags is chosen based on examination of the AIC, SBIC, and the likelihood ratio selection criteria for various choices of p.

I use an unconstrained VAR system to examine the dynamic relation between credit availability, market liquidity, and asset prices in private and public commercial real estate markets over the 1992:Q2 to 2009:Q4 sample period. I utilize data from the Federal Reserve Board's Senior Loan Officer Survey, which captures changes in lending standards for commercial real estate loans, as my primary measure of credit availability. As a proxy for market

liquidity in the private commercial real estate market, I utilize the percentage of properties sold from the National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index each quarter. To capture market liquidity for publicly traded equity REITs, I utilize a price impact measure based on the methodology of Amihud (2002).[2] To capture price changes in private and public commercial real estate, I utilize the percentage price change in the quarterly MIT/NCREIF Transaction Based Index (TBI) and the appreciation component of the FTSE NAREIT U.S. equity REIT index, respectively. I include lagged values of several macroeconomic variables and risk proxies that have been shown to matter in the asset pricing literature to control for other potential sources of variation in market liquidity, credit availability and asset prices over time as described further in the data section.

Data and Descriptive Statistics

Liquidity Data Sources and Definitions

In a relatively illiquid market, such as private commercial real estate, transaction frequency is a key indicator of market liquidity (Fisher et al., 2004). When there are more potential buyers in the market, property owners can sell more assets, or sell any given asset more quickly, with less of an impact on competitively determined market values. Conversely, when market liquidity is low, asset turnover will be lower and the price impact of a transaction will be relatively high.

I measure aggregate market liquidity in the private commercial real estate market using the percentage of properties sold (PROPSOLD) from the NCREIF NPI index. Established in 1982, NCREIF is a not-for-profit institutional real estate industry association that collects, processes, validates, and disseminates information on the risk/return characteristics of commercial real estate assets owned by institutional (primarily pension fund) investors. NCREIF's flagship index,

[2] Results from Augmented Dickey Fuller Tests suggest the use of first differences of measures of credit availability and market liquidity in the VAR specifications.

the NCREIF Property Index (NPI), tracks property-level returns on a large pool of commercial real estate assets acquired in the private market for investment purposes only. The property composition of the NPI changes quarterly as data contributing NCREIF members buy and sell properties. However, all historical property-level data remain in the database and index. An increase in PROPSOLD suggests that market liquidity in the private commercial real estate market is increasing. As a robustness check, I also construct an additional measure of market liquidity for the private commercial real estate market, TBI_LIQ. TBI_LIQ is the difference between the variable liquidity TBI supply index and the constant-liquidity TBI demand index. The contemporaneous correlation between PROPSOLD and TBI_LIQ is 0.79.

In a relatively liquid market, such as the market for publicly traded shares of REIT common equity, market liquidity measures are directly observable. Using daily price and share volume data obtained from the University of Chicago's Center for Research in Security Prices (CRSP), I construct a price impact measure of market liquidity for REIT common equity based on the methodology of Amihud (2002). REIT_LIQ is a value-weighted index constructed from the daily ratio of absolute stock return to dollar volume, averaged over the quarter in which shares were traded. I use the additive inverse of the Amihud (2002) measure so that an increase in REIT_LIQ represents an increase in market liquidity within the public REIT market. In my empirical analysis, I utilize the natural log of REIT_LIQ. As a robustness check, I also construct a share turnover measure for publicly traded common shares of equity REITs using daily trading volume and shares outstanding from CRSP. I define REIT_TURN as total trading volume in a quarter divided by total shares outstanding as of the end of the quarter.[3]

[3] Barinov (2010) suggests that share turnover proxies for firm-specific uncertainty rather than market liquidity. Therefore, I utilize my price impact measure, REIT_LIQ, as the primary measure of market liquidity for the public real estate market within the empirical analysis.

Credit availability is defined as the ease with which an investor can obtain capital for acquisitions and the refinancing of existing assets. Because bank lending standards are the criteria by which banks evaluate the risk of providing credit to potential borrowers, changes in these standards reflect the relative ease with which investors may obtain funds. All else equal, a tightening in lending standards would reduce the supply of funds available to investors and therefore decrease the availability of credit.

To measure credit availability in the commercial real estate market, I obtain a quarterly survey of approximately sixty large domestic banks and twenty-four U.S. branches or agencies of foreign banks from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The purpose of the survey is to collect information on credit availability, with a focus on changes in lending practices within domestic loan markets. The sample of respondents is geographically diverse as participating banks come from all 12 Federal Reserve Districts. The banks must also have more than $3 billion in assets and more than 5% of their loan portfolio comprised of commercial and industrial (C&I) loans. While the survey was originally created in 1967, there have been several breaks in the time series and some variation in the wording of its questions. Since the second quarter of 1990, however, the survey has maintained consistency in its core set of questions.

To construct a measure of changes in credit availability, I focus on responses to the following survey question: "Over the past three months, how have your bank's credit standards for approving applications for commercial real estate loans changed?" Respondents must select one of the following options: tightened considerably, tightened somewhat, remained essentially unchanged, eased somewhat, or eased considerably. I define TIGHTEN as the net percentage of loan officers reporting a tightening of credit conditions. More specifically, it is the sum of the

number of respondents who selected “tightened considerably” and “tightened somewhat” minus the sum of the number of respondents who selected “eased somewhat” or “eased considerably” divided by the total number of respondents. An increase in TIGHTEN indicates that the availability of funds for commercial real estate investment is declining. Lown, Morgan, and Rohatgi (2000) show that lending by U.S. banks slows substantially following a report of tightened lending standards in the Senior Loan Officer Survey and that reported changes in lending standards are highly correlated with other measures of credit availability.

An additional measure of credit availability within commercial real estate markets, RERC_CAPITAL, is constructed from survey data published by the Real Estate Research Corporation (RERC) in its quarterly Real Estate Report. RERC surveys institutional real estate investors, appraisers, lenders, and managers throughout the United States to gather information on current investment criteria, such as required rates of return on equity, expected rental growth rates, and current investment conditions, including the availability of capital. RERC survey respondents are asked to rank the current availability of capital for investment on a scale of 1 to 10, with 1 indicating “poor” capital availability and 10 indicating “excellent” access to capital. I transform the RERC measure to be consistent with the definition of TIGHTEN by taking the additive inverse, centering the series on zero, and expressing values as a percentage. An increase in RERC_CAPITAL therefore indicates that respondents believe capital availability has decreased over the prior quarter.

Asset Pricing Data Sources and Definitions

To measure price changes in the private commercial real estate market, I utilize the TBI (Transactions–Based Index of Industrial Commercial Property Investment Performance) price index. The TBI is a hedonic price index based on a "representative property" that mirrors the average characteristics of the NCREIF properties. The TBI price index estimates quarterly

market price changes based on the verifiable sales prices of properties sold from the NCREIF database each quarter.[4] I utilize the natural log of the quarterly percentage change in the aggregate price index (TBIRET) as a measure of asset price movements in the private commercial real estate market. For robustness, I also utilize the natural log of the quarterly capital return component of the leveraged NCREIF index (NCREIF_LEV) as an additional measure of asset price movements in the private commercial real estate market. The correlation between the capital return component of the leveraged NCREIF and the change in the TBI price index is 0.62.

Pricing data for common shares of publicly traded commercial real estate is obtained from the National Association of Real Estate Investment Trusts (NAREIT). Members of NAREIT include REITs that own, operate and finance income-producing real estate. NAREIT publishes the FTSE NAREIT Equity Index, a market capitalization weighted index measuring returns on REITs that meet minimum size and liquidity criteria and are listed on the NYSE/Amex or Nasdaq. I utilize the natural log of the quarterly appreciation component of the return on the FTSE NAREIT Equity Index (REITRET) as a measure of asset price movements in the public commercial real estate market.

Control Variables

I include the following set of control variables to capture other potential sources of variation in prices, credit availability, and market liquidity in the VAR regression specifications: the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), the rate of inflation (INFLA), and the excess return on the

[4] Details of the index methodology are described in Fisher, Geltner, and Pollakowski (2007).

public stock market (MKT) (e.g., Chen, Roll, and Ross, 1986; Ferson and Harvey, 1991; Fama and French, 1993; Fama and Schwert, 1977; Sharpe, 2002). In addition, I include the remaining Fama-French risk factors, SMB and HML, augmented by the return momentum factor, UMD (e.g., Fama and French 1996; Liew and Vassalou, 2000; Lettau and Ludvigson, 2001; Jegadeesh and Titman, 1993; and Carhart, 1997). These factors also control for the public equity characteristics of the public market real estate returns.

Prior research has shown that dividend (current) yields are also a significant predictor of subsequent asset price changes (Ghysels, Plazzi and Valkanov, 2007; Fama and French, 1988). Therefore, I include the dividend yield on equity REITs (DIVYLD) as an additional control variable in the REIT pricing equations. In the private market specifications, I use the aggregate capitalization rate (CAPRT) for commercial properties (i.e., the ratio between a property's annual net rent and its price) to proxy for current yield. Dividend yields and capitalization rates are obtained from NAREIT and the American Council of Life Insurers (ACLI), respectively.

Descriptive Statistics

Table 3-1 reports descriptive statistics for each measure of credit availability, market liquidity, price returns, and control variables over the 1992:Q2 to 2009:Q4 sample period. The starting point of the sample period is dictated by the availability of survey data obtained from the Real Estate Research Corporation (RERC). When responding to the Senior Loan Officer Survey, loan officers are instructed to report changes in lending standards over the previous quarter regardless of how current credit conditions compare to long-term norms. Nevertheless, TIGHTEN, displays a high degree of autocorrelation (0.91), indicating persistence in the direction of changes in lending standards over time. RERC_CAPITAL displays a similar level of autocorrelation (0.95). Though highly autocorrelated, both measures capture significant peaks and troughs in credit availability cycles. For example, TIGHTEN ranges from a minimum of

-0.24, indicating that the net percentage of respondents reported an easing in lending standards, to a high of 0.87, denoting a period in which most banks were tightening lending standards. RERC_CAPITAL displays similar variation ranging from a low of -0.911 to a high of 0.822. The contemporaneous correlation between RERC_CAPITAL and TIGHTEN is 0.65 (Table 3-2). In reference to the latest credit cycle, both proxies capture a substantial loosening in credit standards over the 2001 to 2005 real estate boom and a sharp increase in credit standards during the market downturn in 2007 and 2008.

The second panel of Table 3-1 reports descriptive statistics for measures of market liquidity in private and public commercial real estate markets. On average, only 2.1% of the properties held in the NCREIF database are sold each quarter over the sample period, indicating that private commercial real estate markets are extremely illiquid. PROPSOLD also displays a high degree of autocorrelation (0.64), indicating persistence in periods of relative illiquidity. The average daily ratio of absolute REIT stock returns to dollar volume is 1.149. REIT_LIQ displays significant volatility over the sample period. That is, even relatively liquid public markets experience significant declines in market liquidity when investors face difficulties obtaining funds for investment.

Panels A and B of Figure 3-1 display TIGHTEN and aggregate measures of market liquidity in the private commercial real estate market (PROPSOLD) and public commercial real estate market (REIT_LIQ), respectively. Following a period of large declines in commercial real estate values and a credit crunch in the late 1980s and early 1990s, lending standards for commercial real estate loans were eased slightly in late 1993 and remained relatively loose for several years. During this period, the public REIT market was growing significantly with increased involvement from institutions. Institutional investors, who had difficulty disposing of

properties within the private market during the downturn of the late 1980s, were shifting funds into the liquid market for publicly traded REITs. As funds continued to flow into the public commercial real estate sector, market liquidity in the underlying property market also increased significantly over this period. Lending standards for commercial real estate loans began to tighten again in the late 1990s, a period in which many investors rotated out of value-oriented assets, including commercial real estate, and into high growth technology stocks. Not surprisingly, a significant shock to market liquidity in private commercial real estate occurred. Following an easing of lending standards in 2002, commercial real estate prices and market liquidity significantly increased. However, as the credit crisis began to unfold in late 2007 to 2008, lending standards on commercial real estate loans were tightened considerably. Market liquidity plunged in subsequent quarters within both private and public real estate markets.

The third panel of Table 3-1 reports descriptive statistics for each price return series. Consistent with prior literature, the average quarterly return on publicly traded equity REITs (1.5%) is greater than returns on similar institutional quality assets owned and managed in private markets (TBIRET = 0.8%). However, price changes in the public REIT market are substantially more volatile than those in the underlying private property market[5].

The final panel of Table 3-1 reports descriptive statistics for each control variable. The annual yield on three-month Treasury bills (TBILL) averaged 3.60% over the sample period, ranging from a low of 0.10% to a high of 6.2%. The slope of the Treasury term structure averaged 1.7% on an annual basis, although TERMSPREAD varied significantly over the sample period. The mean default risk premium is 0.90% per year, but DEFSPREAD ranged from a low of just 0.60% to a high of 3.0%. Average quarterly inflation (INFLA) is 0.60%, although

[5] Mean and standard deviation of private market returns using NCREIF_LEV are -0.1% and 5.0%, respectively.

inflation also displayed considerable time variation over the sample period. The mean stock market risk premium (MKT) is 1.50% per quarter, but ranges from a low of -22.3% to a high of 20.6%. SMB, HML, and UMD averaged 0.90%, 0.80%, and 1.7% per quarter, respectively, and also displayed substantial volatility over the sample period. The average cap rate (CAPRT) for commercial properties over the sample period is 8.60%, ranging from a low of 6.50% to a high of 10.3%. The mean dividend yield (DIVYLD) for equity REITs is 6.30% and ranges from 3.60% to 9.40%.

Table 3-2 reports contemporaneous correlations among measures of credit availability and price appreciation. Credit availability (TIGHTEN) is negatively related to TBIRET (ρ = -0.47) and REITRET (ρ = -0.28). That is, a tightening of lending standards for commercial real estate loans is unconditionally correlated with a decline in asset values within both private and public commercial real estate markets. I find similar results using RERC_CAPITAL.

Panel A of Figure 3-2 displays TIGHTEN in relation to TBIRET. Beginning in 2002, when lending standards were eased considerably, prices in private commercial real estate experienced a significant boom. However, as credit availability decreased in 2005, prices began to spiral as returns declined consistently over the next two years. Thus, unconditionally, changes in lending standards and price changes appear to reinforce each other in the private market.

Panel B of Figure 3-2 plots TIGHTEN against REIT returns (REITRET). Although REIT returns appear to respond to changes in lending standards, they quickly revert in subsequent periods. For example, while REIT prices experienced a significant decline in the fourth quarter of 2008, prices rebounded quickly in the first quarter of 2009.

Empirical Results

Dynamic Relations in Illiquid Private Markets

Table 3-3 provides estimates of an unconstrained VAR model for the private commercial real estate market in which the percentage change in the TBI price index (TBIRET), changes in credit availability (ΔTIGHTEN), and changes in aggregate market liquidity (ΔPROPSOLD) are specified as endogenous variables. Although the coefficient estimates are not reported, I also include lagged values of the following exogenous control variables: TBILL, TERMSPREAD, DEFSPREAD, INFL, MKT, SMB, HML, UMD, and CAPRT. The sample period is 1992:Q2 to 2009:Q4. Utilizing this specification, I test whether changes in credit availability affect subsequent market liquidity and whether a feedback effect occurs in which changes in market liquidity affect the subsequent availability of credit, controlling for lagged fundamentals and other factors. As previously discussed, when access to credit markets is tightened, investors find it more difficult to finance acquisitions or to refinance previously acquired assets. This is especially true of highly levered assets. The lack of credit availability subsequently lowers market liquidity. Under certain conditions, reduced market liquidity increases the risk of financing a transaction, thus leading to further tightening in the availability of credit to these investors (Brunnermeier and Pedersen, 2009). When credit conditions continue to tighten in illiquidity, they are said to be "destabilizing," and a liquidity spiral may ensue.

Focusing first on the ΔPROPSOLD equation (Column 3), I find that an increase in credit tightening predicts a decrease in market liquidity with either a two-quarter (p-value = 0.079) or three quarter lag (p-value = 0.073). That is, as the percentage of banks tightening commercial real estate lending standards increases, the percentage of properties sold in the private commercial real estate market declines in subsequent quarters. Although not tabulated, I find a

similar relation between changes in the availability of capital and changes in subsequent market liquidity using ΔRERC_CAPITAL as an alternative measure of credit availability.

If shifts in market liquidity further reduce the availability of credit, a liquidity spiral may arise. In the ΔTIGTHEN equation (Column 2), the estimated coefficient on the two-quarter lag of ΔPROPSOLD is negatively related (p-value = 0.045) to ΔTIGTHEN. Thus, consistent with the theory of Brunnermeier and Pedersen (2009), preliminary results suggest that a tightening in lending standards can lead to a liquidity (margin) spiral in the private commercial real estate market as decreasing market liquidity further reduces the supply of credit. I find similar results using ΔTBI_LIQ as my measure of market liquidity in the private real estate market.

The VAR specification also allows for a test of whether changes in credit availability affect subsequent price movements in private real estate markets and whether a feedback effect occurs in which price changes affect the subsequent availability of credit. When changes in lending standards and market liquidity are "destabilizing," there may be a magnification in the price impact of subsequent transactions in the form of a loss spiral. Both types of liquidity spirals reinforce each other, amplifying the total effect beyond what their individual impacts would be (Brunnermeier and Pedersen, 2009; Brunnermeier, 2009; Geanakoplos, 2003).

Focusing on the TBIRET equation (Column1), the estimated coefficients on ΔTIGHTEN at the two- and three-quarter lags are negative and highly significant. This strongly suggests that a tightening of lending standards leads to price declines over subsequent periods. This result is consistent with the theoretical predications of Brunnermeier and Pedersen (2009) and Geanakoplos (2003). When assets can be readily acquired using significant leverage, the most optimistic investors are able to own and control a larger percentage of the current stock of assets than they would be able to otherwise. However, as the capital available to these optimistic buyers

declines, they are less able to acquire or refinance assets, thereby leaving more pessimistic investors as the marginal buyers. As a result, asset valuations will likely decline. This important result is robust to the use of ΔRERC_CAPITAL in place of ΔTIGHTEN.

The estimated coefficient on lagged TBIRET in the TBIRET equation is negative (-0.235) and significant (p-value = 0.076), indicating that price increases in the prior quarter predict a subsequent reversal in the following quarter. However, if changes in asset values impact the availability of capital to make future transactions, prices may spiral in one direction.

Returning to the ΔTIGHTEN equation (Column 2), I find a negative (-1.079) and highly significant (p-value = 0.000) relation between lagged TBIRET and current period ΔTIGHTEN. That is, declining asset prices in a relatively illiquid market increase the risk of financing another trade, which leads banks to further tighten the supply of available credit for future transactions. Consistent with the theory of Brunnermeier and Pedersen (2009), these results imply that a decrease in credit availability can lead to a liquidity (loss) spiral in the private commercial real estate market as a decrease in asset prices affects the supply of credit in the subsequent quarter.

Although not tabulated, I find similar results when using NCREIF_LEV as an alternative measure of price changes in the private commercial real estate market. In the NCREIF_LEV equation, the estimated coefficients on lagged ΔTIGHTEN are negative and highly significant. In the ΔTIGHTEN equation, I again document a feedback effect in which the estimated coefficient on lagged NCREIF_LEV is negative and significantly related to subsequent period ΔTIGHTEN.

To examine the cumulative effect of all four lags of the endogenous variables, I sum the estimated lagged coefficients and test whether the four lags are jointly significant. The summed coefficients and p-values associated with tests of joint significance are reported in Table 3-4. Controlling for aggregate market liquidity, a tightening of lending standards over the prior year

predicts price declines in the private market. Moreover, declining prices are associated with a subsequent tightening of lending standards. Reduced market liquidity over the prior four quarters is also associated with a tightening of credit standards.

Dynamic Relations in Liquid Public Markets

In contrast to their underlying properties, the equity REITs I examine trade frequently on a number of major stock exchanges. Although changes in the availability of credit may still impact market liquidity in these markets, it is less likely that subsequent changes in credit availability will be "destabilizing" when markets are relatively liquid. Temporary shocks to market liquidity create profit opportunities for speculators who anticipate that prices will return to fundamentals once liquidity has been restored. As long as arbitrageurs are far from hitting their funding constraint, then asset prices will be less susceptible to a liquidity (loss) spiral, even if a tightening in credit markets causes market liquidity to decline. Using a VAR analysis, I first test whether changes in the availability of credit affect subsequent market liquidity and whether a feedback effect occurs in which changes in market liquidity affect subsequent credit availability in the relatively liquid market for publicly traded equity REITs. I then examine whether a loss spiral ensues, thereby magnifying the overall price impact of a change in credit availability.

Table 3-5 provides estimates of an unconstrained VAR model for the REIT market in which the appreciation component of the REIT return index (REITRET), changes in credit availability (ΔTIGHTEN), and changes in aggregate REIT market liquidity (ΔREIT_LIQ) are specified as endogenous variables. As in the specifications for the private market, I include the following set of exogenous control variables: TBILL, TERMSPREAD, DEFSPREAD, INFL, MKT, SMB, HML, and UMD. I also include the dividend yield (DIVYLD) on equity REITs, rather than the aggregate cap rate for commercial properties.

Focusing first on the ΔREIT_LIQ equation (Column 3), the estimated coefficient on ΔTIGHTEN at both the one- and two-quarter lags are negative and significant. As investors find it difficult to obtain credit, the price impact of a subsequent transaction increases. Thus, credit tightening is associated with decreased liquidity in the REIT market. In the ΔTIGHTEN equation (Column 2), I find that the two-quarter lag of ΔREIT_LIQ is negatively related to ΔTIGHTEN. Thus, I find further evidence of a liquidity (margin) spiral within the public real estate market.

Turning to the REITRET equation (Column 1), the estimated coefficients on both the three- and four-quarter lag of ΔTIGHTEN are negative and highly significant. Thus, consistent with the private market results, a tightening in lending standards leads to subsequent declines in REIT prices. I again find similar results using ΔRERC_CAPITAL as an alternative measure of credit availability. Overall, these results strongly suggest that changes in credit availability are an important determinant of asset price movements for highly leveraged assets that trade in relatively liquid markets as well.

Recall, Brunnermeier and Pedersen's (2009) theoretical framework suggests that the sensitivity of subsequent changes in credit availability to changes in asset prices is larger for assets that are highly leveraged and relatively illiquid. Because sustained periods of illiquidity are far less common in public markets, one would expect to find less of a feedback effect between asset prices and the availability of credit. Returning to the ΔTIGHTEN equation (Column 2), I do not find a significant relation between prior period REIT returns and changes in credit availability. Therefore, I do not find evidence of a loss spiral using aggregate data for the public real estate market.

To examine the cumulative effect of all four lags of the endogenous variables, I again sum the estimated lagged coefficients and test whether the four lags are jointly significant. The

summed coefficients and p-values associated with tests of joint significance are reported in Table 3-6. Controlling for aggregate market liquidity, a tightening of lending standards over the prior year predicts significant price declines in the REIT market (p-value = 0.001). However, in contrast to the private market results, declining REIT prices do not predict a subsequent tightening of lending standards (Column 2). Furthermore, increases in REIT prices over the prior year predict increased liquidity in the REIT market (Column 3). In contrast, increases in credit tightening significantly reduce REIT market liquidity (p-value = 0.001).

Impulse Response Functions: Credit Availability and Asset Price Movements

Further evidence regarding the impact of changes in credit availability on asset price movements in both private and public commercial real estate markets is provided by the VAR generalized impulse response functions displayed in Figure 3-3. Panels A and B depict the response of quarterly price changes in TBIRET and REITRET, respectively, to a one standard deviation change in my primary measure of credit availability (TIGHTEN). The solid line in each figure represents the estimated diffusion of quarterly price changes to the shock in credit availability. Panels A and B of Figure 3-3 reveal an initial decrease in asset prices in both private and public markets in response to a shock to credit availability. However, there is a significant delay in the time it takes for asset prices to revert following a shock to credit availability within the relatively illiquid private market.

Panels C and D display the response of TIGHTEN to a one standard deviation change in private and public market price changes, respectively. In contrast to the REIT results (Panel D), subsequent credit availability is significantly impacted by a shock to asset prices within the private market (Panel C). As asset prices fall, credit conditions tighten, reinforcing the initial impact of a change in credit availability on asset prices within an illiquid market.

Leverage and Liquidity Portfolio Sorts: Public Market

In private markets, I document a spiral effect between changes in credit availability and property prices. In the REIT market, however, movements in share prices do not appear to reinforce changes in the availability of credit. However, it is possible for such a feedback relationship to exist within a particular cross-section of the REIT market. Brunnermeier and Pedersen's (2009) theoretical framework suggests the feedback between changes in credit availability and asset price movements is stronger for capital intensive assets that are relatively illiquid. Therefore, one might expect to find evidence of a spiral effect among REITs with high leverage and low share turnover.

To test this hypothesis, I obtain leverage and share turnover data for each REIT in the aggregate index using data from SNL and CRSP, respectively. REITs are first sorted into quartiles based on both leverage and liquidity. I then construct value-weighted price return portfolios for each subset of the data. For example, to construct the High Leverage-Low Liquidity portfolio, I create a value-weighted portfolio of REITs that fall into both the highest leverage quartile and lowest share turnover quartile within each quarter of the sample period. On average, the leverage ratios for the high and low leverage portfolios are approximately 60% and 20%, respectively. For the liquidity sorts, average quarterly share turnover is 8% for the low liquidity quartile and 46% for the high liquidity quartile. I follow the empirical methodology detailed previously, utilizing price returns and price impact measures of market liquidity for each portfolio, in addition to the aggregate measure of credit availability, in separate VAR specifications. I include the same set of exogenous control variables as specified previously in the earlier REIT market analysis.

Table 3-7 presents results from the portfolio analysis. For ease of presentation, I report the sum of the coefficient estimates across all four lags and the p-value pertaining to the joint

significance of those four lags. Focusing first on the REITRET equations (Columns 1 and 4), I document a negative and statistically significant relation between changes in credit availability (ΔTIGHTEN) and subsequent REIT returns (REITRET) in each portfolio specification. Moreover, the magnitudes of the estimated coefficients on ΔTIGHTEN are increasing in leverage. In other words, share prices of more highly leveraged REITs are more sensitive to changes in credit availability.

However, I document a feedback effect between changes in REIT price movements and the subsequent availability of credit only for relatively illiquid REITs (Columns 2 and 5). Consistent with my initial hypothesis, the estimated coefficient on REITRET is negative (-1.127) and highly significant (p-value = 0.005) for the High Leverage-Low Liquidity portfolio. In addition, I find evidence of a feedback effect between changes in REIT prices and credit availability for the Low Leverage-Low Liquidity portfolio. However, I do not find evidence of a feedback effect in the High Liquidity portfolios, regardless of leverage ratios. Therefore, the spiral effect is concentrated in the low liquidity REIT portfolios. Consistent with Brunnermeier and Pedersen's (2009) liquidity based theory, relative illiquidity is a necessary condition for a spiral effect to occur. This result is also consistent with my previous results from the private market in which similar assets trade in a relatively illiquid environment.

Using Returns on REIT Preferred Stock as a Robustness Check

Within public stock markets there is also the opportunity to examine two types of equity securities issued by the same firm, each with claims on similar cash flow streams, yet which trade at different prices and with different liquidity. By examining the relation between credit availability and the prices of REIT preferred shares, I provide an alternative test of the sensitivity of asset prices to changes in the availability of capital within a relatively illiquid public market. Having documented the existence of loss spirals in the private market as well as the low liquidity

segment of the public REIT market, I further hypothesize that asset prices of REIT preferred shares may be susceptible to a spiral effect due to the low liquidity environment in which they trade.

I use data from Thomson Reuters DataStream to construct a price index for REIT preferred securities. More specifically, I obtain historical share prices, shares outstanding, trading volume, and market capitalization data for all REIT preferred securities over the sample period. I then construct a quarterly value-weighted index based on the percentage price change of each REIT preferred security (REITPREF).[6]

Preferred shares are often considered a hybrid security because they exhibit both bond- and equity-like characteristics. Nevertheless, the price movements of REIT preferred shares are significantly positively correlated with the returns on equity REIT common shares ($\rho = 0.62$). Similarly, the returns on REIT preferred shares are greater, on average, and more volatile than the returns on private commercial real estate.

Table 3-8 provides estimates of an unconstrained VAR model for the REIT preferred market in which the percentage price change (REITPREF), changes in credit availability (ΔTIGHTEN) and changes in aggregate market liquidity (ΔREITPR_LIQ) are specified as endogenous variables. I include the same set of controls as in prior REIT specifications. Focusing on the REITPREF equation (Column 1), the estimated coefficient on the three quarter lag of ΔTIGHTEN is both negative (-0.193) and highly significant (p-value = 0.001). That is, when access to credit markets is tightened, prices of REIT preferred securities decrease over subsequent quarters. Although not tabulated, I find a similar relation between ΔRERC_CAPITAL and subsequent price returns.

[6] The correlation between my REIT preferred index and the MSCI REIT Preferred Index is 0.98 for the overlapping sample period (2005 to 2009).

I also find evidence of a feedback effect between changes in REIT preferred share prices and the subsequent availability of credit. The estimated coefficient on the one-quarter lag of REITPREF is negative (-0.401) and significant (p-value = 0.026), suggesting that changes in credit availability are sensitive to asset price movements in these relatively illiquid public markets. When using ΔRERC_CAPITAL in place of ΔTIGHTEN, evidence of a feedback effect is even stronger (p-value 0.015). Consistent with Brunnermeier and Pedersen (2009), I find that when funding constraints increase in a relatively illiquid market, subsequent changes in asset prices affect the future availability of capital, thus magnifying the overall price impact of a funding shock.

To examine the cumulative effect of all four lags of the endogenous variables, I again sum the estimated lagged coefficients and test whether the four lags are jointly significant. The summed coefficients and p-values associated with tests of joint significance are reported in Table 3-9. Controlling for aggregate market liquidity, a tightening in credit over the prior year predicts significant price declines in the REIT preferred market (p-value = 0.000). Similar to the private market and low-liquidity portfolio results, reductions in the prices of preferred shares predict a subsequent decrease in the availability of credit (p-value = 0.017). In other words, changes in credit availability are destabilizing in a relatively illiquid market, as changes in asset prices affect the future availability of credit, thus magnifying the overall price impact of a reduction in credit availability. These results provide further evidence of a spiral effect within relatively illiquid segments of the public market.

Credit Availability, Asset Prices, and Investor Sentiment

Anecdotal evidence suggests the expansion of credit availability during the real estate boom of the early-to-mid 2000s was in part driven by the response of creditors to increasing investor optimism and speculative demand for these assets. A recent article in the Economist

(2010) characterizes the emergence of asset pricing bubbles as follows, "Aside from high asset valuations, the two classic symptoms of a bubble are rapid growth in private-sector credit and an outbreak of public enthusiasm for particular assets." Therefore, examining the dynamic relation between changes in the availability of credit and changes in investor sentiment will provide further insight into the underlying factors that fueled the rapid price appreciation and subsequent collapse of the commercial real estate market.

More formally, Shleifer and Vishny (2010) develop a theoretical model in which banks cater their financing decisions to shifts in investor sentiment. During periods of high sentiment, banks increase their mortgage originations (traditional lending), particularly when securitization of these underlying loans is profitable. Banks continue to pursue such profits during a boom period in order to take advantage of attractive money making opportunities in the secondary market. When the asset pricing bubble bursts, banks forgo lending opportunities and credit markets tighten. If investors are unable to access credit precisely at the time it may be most advantageous to do so, and prices continue to fall, a bank's decision to further tighten their lending standards will have a destabilizing effect on prices, similar to the theoretical predictions of Brunnermeier and Pedersen (2009) and Geanakoplos (2003). If banks cater their lending decisions to shifts in investor sentiment, a feedback loop may be created between changes in credit availability and changes in investor sentiment.

In my first study, I construct both a direct and indirect investor sentiment measure for the commercial real estate market. For the direct measure of investor sentiment (DRES), I employ survey data published by the Real Estate Research Corporation (RERC) in its quarterly Real Estate Report. RERC surveys institutional real estate investors, appraisers, lenders, and managers throughout the United States to gather information on current investment criteria, such as

required rates of return on equity, expected rental growth rates, and current "investment conditions." RERC survey respondents are asked to rank current "investment conditions" for multiple property types, both nationally and by metropolitan area, on a scale of 1 to 10, with 1 indicating "poor" investment conditions and 10 indicating "excellent" conditions for investing. DRES is constructed from the first principal component extracted from quarterly RERC investment condition survey responses pertaining to the eight RERC property types. For the indirect measure of sentiment (INDRES), I follow the framework of Baker and Wurgler (2006, 2007) and use principal component analysis to construct an indirect quarterly sentiment index based on the common variation in seven underlying proxies of investor sentiment in commercial real estate markets: (i) the average REIT stock price premium to net asset value (NAV), (ii) the percentage of properties sold each quarter from the National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index (NPI), (iii) the number of REIT IPOs, (iv) the average first-day returns on REIT IPOs, (v) the share of net REIT equity issues relative to total net REIT equity and debt issues, (vi) net commercial mortgage flows as a percentage of GDP, and (vii) net capital flows to dedicated REIT mutual funds. In the subsequent empirical analysis, I utilize the first difference of these series.

To examine the dynamic relation between changes in investor sentiment and changes in the availability of credit, I add changes in investor sentiment as a fourth endogenous variable to my primary VAR specifications. These results are reported in Tables 3-10 and 3-11. For ease of presentation, I again report the sum of the coefficient estimates across all four quarterly lags and the p-value pertaining to the joint significance of those four lags. I report results utilizing aggregate private market return series (TBIRET); however, the results are robust to the use of

aggregate REIT returns. I include the same set of exogenous control variables as specified previously in my earlier private market analysis.

Table 3-10 reports results using the direct measure of investor sentiment (ΔDRES). Focusing first on the TBIRET specification (Column 1), I find that even after controlling for the influence of investor sentiment on asset prices, the estimated coefficient on credit availability ($\Delta TIGHTEN_{t-1 \text{ to } t-4}$) remains negative (-0.217) and statistically significant (p-value = 0.037). In addition, lagged changes in sentiment ($\Delta DRES_{t-1 \text{ to } t-4}$) predict subsequent price changes in the private market, even after controlling for the impact of changes in credit availability and market liquidity. As investors become increasingly optimistic, they bid up prices of these assets in the short-run. I find similar results when using ΔINDRES, as reported in Table 3-11.

Turning to the ΔTIGHTEN equation (Column 2), I continue to observe a feedback effect between changes in property prices and subsequent credit availability after controlling for the impact of investor sentiment. Moreover, increasing sentiment predicts looser underwriting standards. I find similar results using ΔINDRES. Consistent with the hypothesis of Shleifer and Vishny (2010), changes in investor sentiment are a significant determinant of future credit availability. In particular, these results suggest banks respond to increasing investor sentiment by easing their credit standards, thereby making credit more readily available to potential investors when they are most optimistic. However, during a market downturn in which investors are becoming increasingly pessimistic, banks tend to tighten their lending standards, which can have a destabilizing effect on asset prices. This raises an interesting policy implication pertaining to whether lenders have the ability to reduce the probability that an asset pricing bubble emerges by restricting the amount of credit they provide during boom periods or ease the severity of a downturn by making credit available when distressed assets are undervalued.

Finally, looking at the ΔDRES equation (Column 4), there is some evidence of a feedback effect between changes in credit availability and future changes in investor sentiment. However, if I utilize ΔINDRES (Table 3-11), the coefficient on lagged changes in tightening on sentiment is no longer statistically significant.

Summary and Conclusion

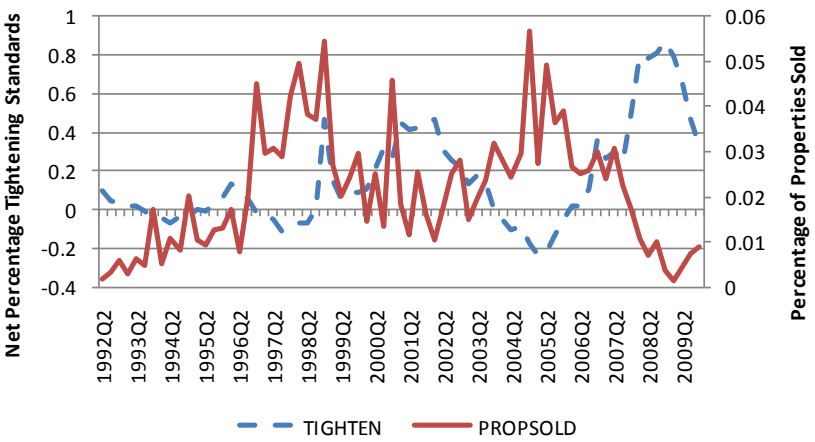
Changes in the availability of credit are a significant determinant of asset price movements in both private and public commercial real estate markets. As credit markets tighten, investors are less able to make new acquisitions in highly leveraged assets and may be forced to de-lever their existing positions by selling assets into an illiquid market, causing prices to decline. When highly leveraged assets trade in relatively illiquid markets, declining asset values may trigger a liquidity (loss) spiral, thereby magnifying the overall price impact of a shock to credit availability.

Commercial real estate markets provide an appealing testing ground for examining the dynamic relation between credit availability, market liquidity, and changes in asset prices. The private commercial real estate market is a relatively illiquid market consisting of highly leveraged assets. Unlike assets traded in more liquid public markets, which tend to experience only brief periods of illiquidity, commercial properties trade in relatively illiquid markets. Therefore, asset prices in this market may be relatively sensitive to changes in credit availability.

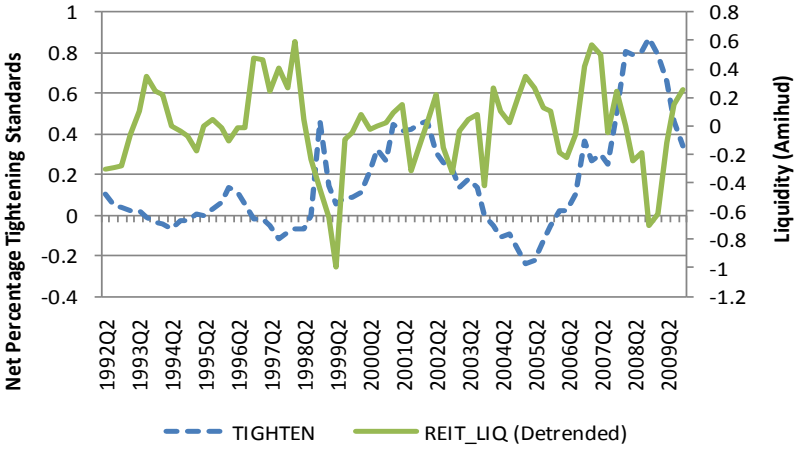
An appealing feature of commercial real estate markets is that assets trade in both a relatively illiquid direct private market and in liquid public stock markets, in the form of securitized portfolios of properties (i.e., REITs). Since the underlying properties held by the publicly traded real estate firms I analyze are similar to the property holdings of the institutional real estate investors whose private market returns I also track, disparities in the impact of funding liquidity on price changes in private and public real estate markets can be ascribed to differences

in the characteristics of these two markets. Therefore, I examine the dynamic relation between changes in credit availability and changes in asset prices within segments of the REIT market that are also relatively illiquid.

Using vector autoregressive (VAR) models, I find that asset values of highly leveraged assets, such as commercial real estate, are sensitive to the availability of credit, even when controlling for aggregate market liquidity. As banks tighten (ease) their lending standards on commercial real estate loans, asset prices decline (rise) in both private and public commercial real estate markets. These results suggest that leverage is a key factor in determining credit market effects on pricing. I also provide evidence that assets trading in illiquid segments of the commercial real estate market are highly susceptible to a spiral effect, in which changes in asset prices lead to further changes in the availability of credit, thus magnifying the overall price impact of a funding shock as a spiral ensues. These results suggest that while leverage plays a significant role in determining credit market availability pricing effects, the underlying liquidity with which these assets trade is a key factor in determining the likelihood of a liquidity (loss) spiral, with lower liquidity creating the market setting for a spiral effect.

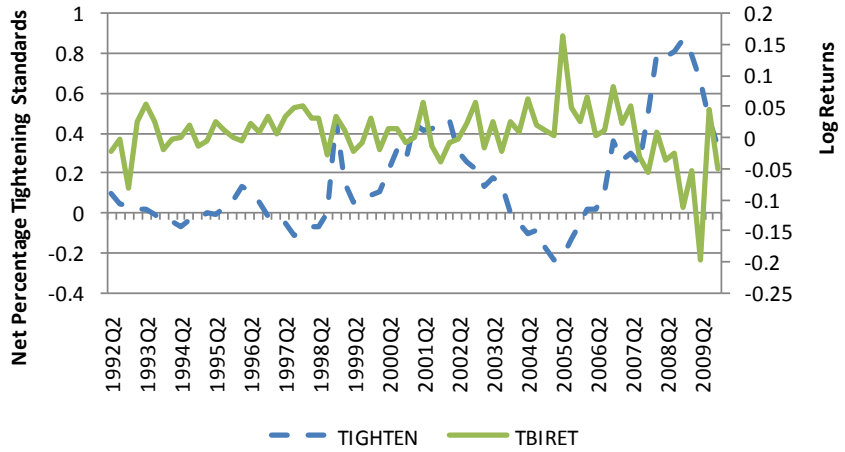


A



B

Figure 3-1. Credit availability and market liquidity. A) This figure plots credit availability and aggregate market liquidity measures in the private commercial real estate market over the sample period 1992:Q2 to 2009:Q4. The measure of credit availability, TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The measure of aggregate market liquidity in the private commercial real estate market, PROPSOLD, is the percentage of properties sold from the NCREIF NPI index. B) This figure plots credit availability and aggregate market liquidity measures in the public commercial real estate market over the sample period 1992:Q2 to 2009:Q4. The measure of credit availability, TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The measure of aggregate market liquidity in the public commercial real estate market, REIT_LIQ, is a price impact measure based on the methodology of Amihud (2002) for equity REITs.



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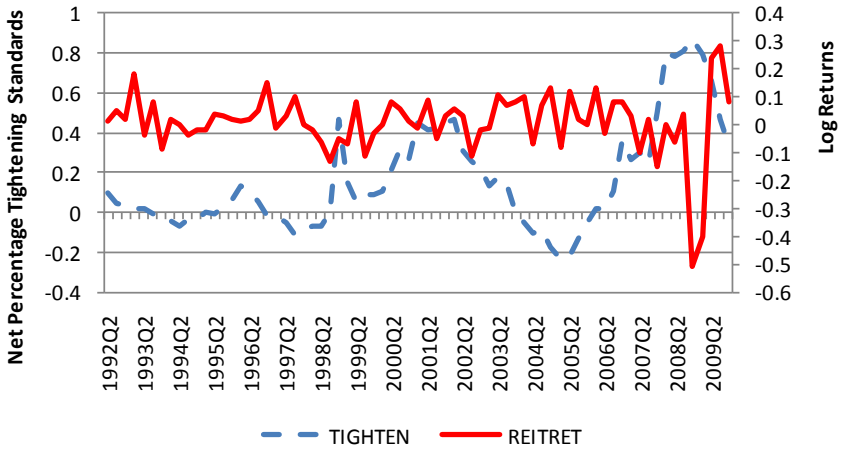
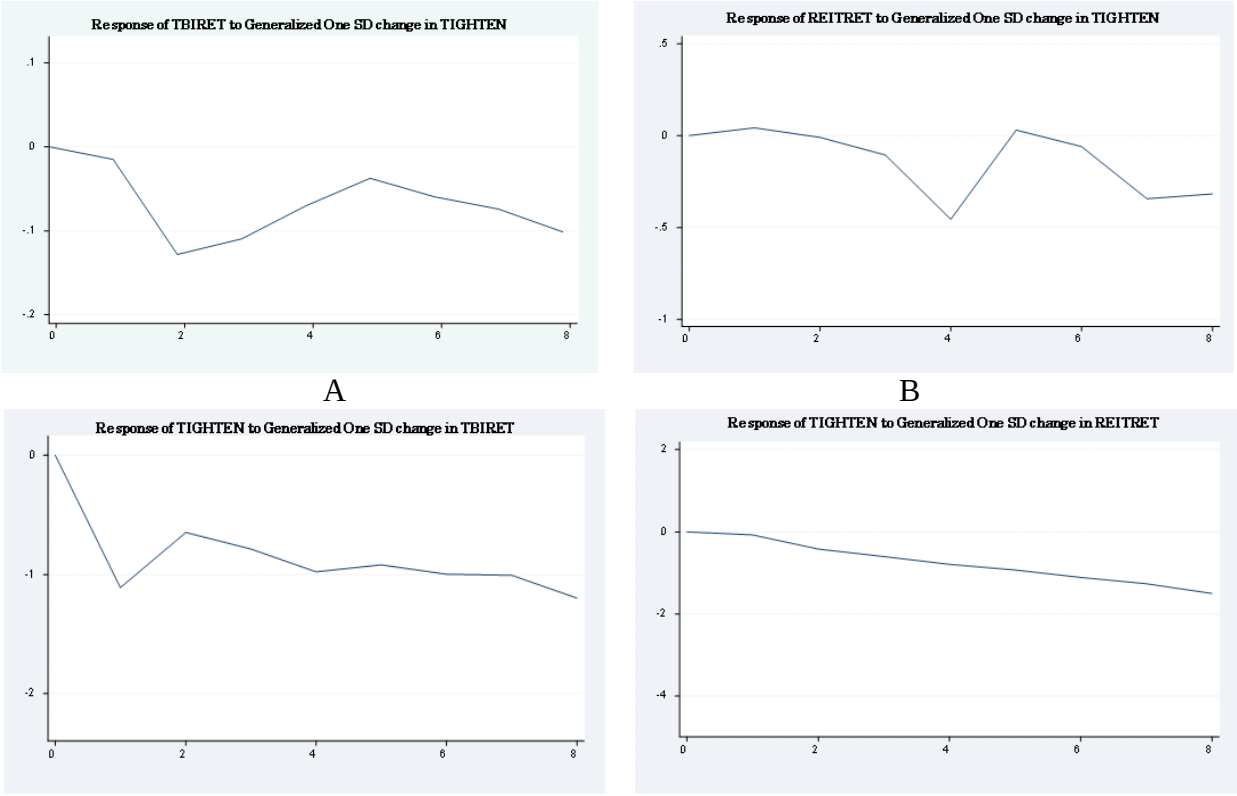


B

Figure 3-2. Credit availability and asset prices. A) This figure plots credit availability and asset price movements in the private commercial real estate market over the sample period 1992:Q2 to 2009:Q4. The measure of credit availability, TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The measure of price changes in the private commercial real estate market, TBIRET, is the natural log of the quarterly percentage change in the aggregate TBI price index produced by the MIT Center for Real Estate in association with the National Council of Real Estate Investment Fiduciaries (NCREIF). B) This figure plots credit availability and asset price movements in the public commercial real estate market over the sample period 1992:Q2 to 2009:Q4. The measure of credit availability, TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. The measure of price changes in the public commercial real estate market, REITRET, is the natural log of the quarterly appreciation component of the return on the FTSE NAREIT Equity Index.



A B C D

Figure 3-3. Impulse response functions: credit availability and price returns. This figure plots the generalized impulse response functions corresponding to estimated VAR models in Table 3-3 and Table3-5 with credit availability measured in changes. The sample period spans 1992:Q2 to 2009:Q4. A) This figure depicts the percentage response in the aggregate price index for private commercial real estate, TBIRET, to a one standard deviation change in credit availability, TIGHTEN. B) This figure depicts the percentage response in the aggregate price index for pubic commercial real estate, REITRET, to a one standard deviation change in credit availability, TIGHTEN. C) This figure depicts the percentage response in the measure of credit availability, TIGHTEN, to a one standard deviation change in the aggregate price index for private commercial real estate, TBIRET. D) This figure depicts the percentage response in the measure of credit availability, TIGHTEN, to a one standard deviation change in the aggregate price index for public commercial real estate, REITRET.

Table 3-1. Descriptive statistics: credit availability, market liquidity, price returns, and controls.

	Variable	Mean	Median	St Dev	Min	Max	Serial Correlation
Credit Availability	TIGHTEN	0.161	0.089	0.263	-0.237	0.870	0.91***
	RERC_CAPITAL	-0.338	-0.467	0.440	-0.911	0.822	0.95***
Market Liquidity	PROPSOLD	0.021	0.020	0.013	0.001	0.057	0.64***
	REIT_LIQ	1.149	1.259	1.005	-1.233	2.789	0.96***
Price Returns	TBIRET	0.008	0.010	0.046	-0.179	0.178	0.18
	REITRET	0.015	0.020	0.106	-0.400	0.320	0.16
Controls	TBILL	0.036	0.039	0.018	0.001	0.062	0.97***
	TERMSPREAD	0.017	0.016	0.012	-0.006	0.036	0.93***
	DEFSPREAD	0.009	0.008	0.005	0.006	0.030	0.85***
	INFLA	0.006	0.006	0.009	-0.039	0.025	-0.14
	MKT	0.015	0.021	0.086	-0.223	0.206	0.08
	SMB	0.009	0.004	0.056	-0.108	0.191	0.03
	HML	0.008	0.004	0.082	-0.320	0.239	0.16
	UMD	0.017	0.019	0.097	-0.398	0.260	0.14
	CAPRT	0.086	0.091	0.010	0.065	0.103	0.95***
	DIVYLD	0.063	0.065	0.014	0.036	0.094	0.87***

This table reports descriptive statistics for measures of credit availability, market liquidity, price returns, and control variables. Mean, median, standard deviation, minimum, maximum, and serial correlation are reported. The primary measure of credit availability, TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey. RERC_CAPITAL is the availability of capital measure published by the Real Estate Research Corporation (RERC) in its quarterly Real Estate Report. Market liquidity in the private commercial real estate market, PROPSOLD, is the percentage of properties sold from the NCREIF NPI index. Market liquidity in the public commercial real estate market, REIT_LIQ, is a price impact measure based on the methodology of Amihud (2002) for the public equity REIT market. The measure of price changes in the private commercial real estate market, TBIRET, is the natural log of the quarterly percentage change in the aggregate TBI price index. The measure of price changes in the public commercial real estate market, REITRET, is the natural log of the quarterly appreciation component of the return on the FTSE NAREIT Equity Index. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), Fama-French factors, MKT, SMB, HML, augmented by momentum (UMD), the aggregate capitalization rate for commercial properties (CAPRT), and the dividend yield on equity REITs (DIVYLD). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-2. Contemporaneous correlations between credit availability and asset price movements.

	TIGHTEN	RERC_CAPITAL	TBIRET	REITRET
TIGHTEN	1.000	0.646***	-0.467***	-0.284**
RERC_CAPITAL		1.000	-0.579***	-0.228*
TBIRET			1.000	0.261**
REITRET				1.000

This table reports contemporaneous correlations between measures of credit availability and price return indices for both private and public commercial real estate markets. The primary measure of credit availability, TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey. RERC_CAPITAL is the availability of capital measure published by the Real Estate Research Corporation (RERC) in its quarterly Real Estate Report. The measure of price changes in the private commercial real estate market, TBIRET, is the natural log of the quarterly percentage change in the aggregate TBI price index. The measure of price changes in the public commercial real estate market, REITRET, is the natural log of the quarterly appreciation component of the return on the FTSE NAREIT Equity Index. The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-3. Credit availability and private commercial real estate: individual lags.

End. Variables	TBIRET	ΔTIGHTEN	ΔPROPSOLD
Constant	0.169**	0.852***	-0.009
	(0.015)	(0.000)	(0.591)
$TBIRET_{t-1}$	-0.235*	-1.079***	0.016
	(0.076)	(0.000)	(0.615)
$TBIRET_{t-2}$	0.165	-0.185	0.030
	(0.180)	(0.424)	(0.322)
$TBIRET_{t-3}$	-0.228	-0.118	-0.035
	(0.150)	(0.692)	(0.356)
$TBIRET_{t-4}$	-0.103	-0.622**	-0.013
	(0.466)	(0.019)	(0.714)
$\Delta TIGHTEN_{t-1}$	0.013	-0.195**	-0.015
	(0.779)	(0.021)	(0.179)
$\Delta TIGHTEN_{t-2}$	-0.099**	-0.175*	-0.020*
	(0.038)	(0.051)	(0.079)
$\Delta TIGHTEN_{t-3}$	-0.099**	-0.248***	-0.021*
	(0.043)	(0.007)	(0.073)
$\Delta TIGHTEN_{t-4}$	-0.056	-0.292***	-0.015
	(0.295)	(0.004)	(0.241)
$\Delta PROPSOLD_{t-1}$	0.043	-1.387	-0.850***
	(0.935)	(0.165)	(0.000)
$\Delta PROPSOLD_{t-2}$	0.760	-2.408**	-0.638***
	(0.233)	(0.045)	(0.000)
$\Delta PROPSOLD_{t-3}$	1.073	0.195	-0.408**
	(0.107)	(0.876)	(0.012)
$\Delta PROPSOLD_{t-4}$	0.092	0.863	-0.093
	(0.867)	(0.403)	(0.485)
Adjusted R^2	0.22	0.55	0.30

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity and price return measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity within the VAR system. Coefficients and p-values are reported for each lag length of the endogenous variables. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. PROPSOLD, is the percentage of properties sold from the NCREIF NPI index. TBIRET, is the natural log of the quarterly percentage change in the aggregate TBI price index. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), and the aggregate capitalization rate for commercial properties (CAPRT). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-4. Credit availability and private commercial real estate: cumulative effect and joint significance.

End. Variables	TBIRET	ΔTIGHTEN	ΔPROPSOLD
$TBIRET_{t-1 \text{ to } t-4}$	-0.195*	-2.004***	-0.002
	(0.074)	(0.000)	(0.740)
$\Delta TIGHTEN_{t-1 \text{ to } t-4}$	-0.243*	-0.910***	-0.072
	(0.074)	(0.002)	(0.128)
$\Delta PROPSOLD_{t-1 \text{ to } t-4}$	1.969	-2.737**	-1.989***
	(0.312)	(0.035)	(0.000)
Adjusted R^2	0.22	0.55	0.30

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity and price return measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity within the VAR system. Summed coefficients and p-values from a joint significance test are reported for each endogenous variable. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. PROPSOLD, is the percentage of properties sold from the NCREIF NPI index. TBIRET, is the natural log of the quarterly percentage change in the aggregate TBI price index. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), and the aggregate capitalization rate for commercial properties (CAPRT). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-5. Credit availability and public commercial real estate: individual lags.

End. Variables	REITRET	ΔTIGHTEN	ΔREIT_LIQ
Constant	-0.041	0.617***	-0.291
	(0.780)	(0.000)	(0.473)
$REITRET_{t-1}$	0.111	0.054	1.203**
	(0.614)	(0.786)	(0.047)
$REITRET_{t-2}$	0.118	-0.171	0.591
	(0.491)	(0.266)	(0.209)
$REITRET_{t-3}$	0.074	-0.150	0.817**
	(0.580)	(0.215)	(0.027)
$REITRET_{t-4}$	0.131	-0.102	0.746**
	(0.324)	(0.390)	(0.041)
$\Delta TIGHTEN_{t-1}$	0.055	-0.293***	-0.503*
	(0.615)	(0.003)	(0.094)
$\Delta TIGHTEN_{t-2}$	-0.101	-0.295***	-1.256***
	(0.372)	(0.004)	(0.000)
$\Delta TIGHTEN_{t-3}$	-0.305**	-0.206*	-0.253
	(0.017)	(0.073)	(0.473)
$\Delta TIGHTEN_{t-4}$	-0.540***	-0.298**	-0.372
	(0.000)	(0.011)	(0.299)
$\Delta REIT\_LIQ_{t-1}$	0.019	-0.049	-0.318**
	(0.694)	(0.265)	(0.018)
$\Delta REIT\_LIQ_{t-2}$	-0.037	-0.106**	-0.303**
	(0.442)	(0.015)	(0.022)
$\Delta REIT\_LIQ_{t-3}$	0.021	-0.044	-0.325***
	(0.636)	(0.270)	(0.008)
$\Delta REIT\_LIQ_{t-4}$	-0.080*	0.021	-0.168
	(0.065)	(0.595)	(0.158)
Adjusted R^2	0.30	0.42	0.11

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity and price return measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity within the VAR system. Coefficients and p-values are reported for each lag length of the endogenous variables. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. REIT_LIQ is a price impact measure based on the methodology of Amihud (2002) for the public equity REIT market. REITRET is the natural log of the quarterly appreciation component of the return on the FTSE NAREIT Equity Index. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), the dividend yield on equity REITs (DIVYLD), and market liquidity in the private commercial real estate market (PROPSOLD). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-6. Credit availability and public commercial real estate: cumulative effect and joint significance.

End. Variables	REITRET	ΔTIGHTEN	ΔREIT_LIQ
$REITRET_{t\text{-}1 \text{ to } t\text{-}4}$	0.435	-0.369	3.356*
	(0.865)	(0.352)	(0.068)
$\Delta TIGHTEN_{t\text{-}1 \text{ to } t\text{-}4}$	-1.000***	-1.092***	-2.384***
	(0.001)	(0.001)	(0.001)
$\Delta REIT\_LIQ_{t\text{-}1 \text{ to } t\text{-}4}$	-0.076	-0.178	-1.114**
	(0.165)	(0.115)	(0.028)
Adjusted R^2	0.30	0.42	0.11

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity and price return measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity within the VAR system. Summed coefficients and p-values from a joint significance test are reported for each endogenous variable. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. REIT_LIQ is a price impact measure based on the methodology of Amihud (2002) for the public equity REIT market. REITRET is the natural log of the quarterly appreciation component of the return on the FTSE NAREIT Equity Index. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), the dividend yield on equity REITs (DIVYLD), and market liquidity in the private commercial real estate market (PROPSOLD). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-7. Credit availability and public commercial real estate: leverage and liquidity sorts.

		Low Leverage			High Leverage		
	End. Variables	REITRET	ΔTIGHTEN	ΔREIT_LIQ	REITRET	ΔTIGHTEN	ΔREIT_LIQ
Low Liquidity	$REITRET_{t\text{-}1 \text{ to } t\text{-}4}$	-0.132	-1.062***	6.070	0.740	-1.127***	-0.639**
		(0.288)	(0.004)	(0.154)	(0.151)	(0.005)	(0.021)
	$\Delta TIGHTEN_{t\text{-}1 \text{ to } t\text{-}4}$	-0.527***	-0.874***	-2.310	-1.744***	-0.452	-0.904**
		(0.006)	(0.002)	(0.128)	(0.000)	(0.137)	(0.028)
	$\Delta REIT\_LIQ_{t\text{-}1 \text{ to } t\text{-}4}$	0.074	0.038	-0.829***	-0.088**	0.083	-0.478***
		(0.169)	(0.704)	(0.000)	(0.004)	(0.750)	(0.000)
	Adjusted R^2	0.09	0.44	0.47	0.43	0.43	0.18
High Liquidity	$REITRET_{t\text{-}1 \text{ to } t\text{-}4}$	-0.004	-0.480	0.233	-0.486	-0.383	1.020
		(0.730)	(0.265)	(0.605)	(0.265)	(0.108)	(0.311)
	$\Delta TIGHTEN_{t\text{-}1 \text{ to } t\text{-}4}$	-0.965***	-0.789**	2.056	-2.169***	-0.710**	0.145
		(0.000)	(0.023)	(0.332)	(0.000)	(0.026)	(0.165)
	$\Delta REIT\_LIQ_{t\text{-}1 \text{ to } t\text{-}4}$	0.065	-0.059	-1.245***	0.493*	0.074	0.894***
		(0.146)	(0.326)	(0.000)	(0.052)	(0.764)	(0.003)
	Adjusted R^2	0.22	0.38	0.22	0.29	0.37	0.06

This table presents results obtained from estimating unrestricted VAR models on a series of REIT portfolios. Securities are assigned to portfolios based on quartile sorts on leverage ratios and share turnover. The lag-length of the VAR is chosen by looking at AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity in the VAR system. Summed coefficients and p-values from a joint significance test are reported for each endogenous variable. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. REIT_LIQ is a price impact measure based on the methodology of Amihud (2002) for a value-weighted portfolio of equity REIT securities in each quartile. REITRET is the natural log of the quarterly appreciation component of the return on a value-weighted portfolio of REIT securities in each quartile. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), the dividend yield on equity REITs (DIVYLD), and market liquidity in the private commercial real estate market (PROPSOLD). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-8. Credit availability and public commercial real estate: preferred equity individual lags.

End. Variables	REITPREF	ΔTIGHTEN	ΔREITPR_LIQ
Constant	-0.168**	0.662***	-0.949
	(0.028)	(0.000)	(0.279)
$REITPREF_{t-1}$	0.226**	-0.401**	-0.324
	(0.038)	(0.026)	(0.796)
$REITPREF_{t-2}$	0.070	-0.318	0.298
	(0.555)	(0.104)	(0.826)
$REITPREF_{t-3}$	-0.290***	-0.429**	1.514
	(0.007)	(0.016)	(0.223)
$REITPREF_{t-4}$	0.180*	-0.077	-0.022
	(0.090)	(0.662)	(0.985)
$\Delta TIGHTEN_{t-1}$	-0.035	-0.270***	-1.025
	(0.536)	(0.004)	(0.115)
$\Delta TIGHTEN_{t-2}$	-0.031	-0.262***	0.718
	(0.596)	(0.006)	(0.280)
$\Delta TIGHTEN_{t-3}$	-0.193***	-0.106	-1.259*
	(0.001)	(0.280)	(0.065)
$\Delta TIGHTEN_{t-4}$	-0.400***	-0.224**	-0.471
	(0.000)	(0.050)	(0.553)
$\Delta REITPR\_LIQ_{t-1}$	-0.002	-0.029	-0.261**
	(0.886)	(0.127)	(0.047)
$\Delta REITPR\_LIQ_{t-2}$	-0.022*	-0.023	0.164
	(0.054)	(0.223)	(0.214)
$\Delta REITPR\_LIQ_{t-3}$	0.047***	-0.010	0.136
	(0.000)	(0.552)	(0.225)
$\Delta REITPR\_LIQ_{t-4}$	0.030***	0.016	-0.496***
	(0.002)	(0.327)	(0.000)
Adjusted R^2	0.54	0.40	0.27

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity and price return measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity within the VAR system. Coefficients and p-values are reported for each lag length of the endogenous variables. TIGHTEN is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. REITPR_LIQ is a price impact measure based on the methodology of Amihud (2002) for REIT preferred shares. REITPREF is a quarterly value-weighted price index for REIT preferred securities constructed using data from Thomson Reuters Datastream. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), the dividend yield on equity REITs (DIVYLD), and market liquidity in the private commercial real estate market (PROPSOLD). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-9. Credit availability and public commercial real estate: preferred equity cumulative effect and joint significance.

End. Variables	REITPREF	ΔTIGHTEN	ΔREITPR_LIQ
$REITPREF_{t-1 \text{ to } t-4}$	0.186***	-1.225**	1.466
	(0.005)	(0.017)	(0.790)
$\Delta TIGHTEN_{t-1 \text{ to } t-4}$	-0.659***	-0.861***	-2.037
	(0.000)	(0.003)	(0.117)
$\Delta REITPR\_LIQ_{t-1 \text{ to } t-4}$	0.053***	-0.046	-0.457***
	(0.000)	(0.420)	(0.000)
Adjusted R^2	0.54	0.40	0.27

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity and price return measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability and market liquidity within the VAR system. Summed coefficients and p-values from a joint significance test are reported for each endogenous variable. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. REITPR_LIQ is a price impact measure based on the methodology of Amihud (2002) for REIT preferred shares. REITPREF is a quarterly value-weighted price index for REIT preferred securities constructed using data from Thomson Reuters Datastream. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), the dividend yield on equity REITs (DIVYLD), and market liquidity in the private commercial real estate market (PROPSOLD). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-10. Credit availability and investor sentiment using a direct sentiment measure.

End. Variables	TBIRET	ΔTIGHTEN	ΔPROPSOLD	ΔDRES
$TBIRET_{t\text{-}1 \text{ to } t\text{-}4}$	-0.114**	-1.451**	-0.014	-0.836
	(0.036)	(0.039)	(0.715)	(0.248)
$\Delta TIGHTEN_{t\text{-}1 \text{ to } t\text{-}4}$	-0.217**	-0.953***	-0.066	-1.831*
	(0.037)	(0.000)	(0.136)	(0.053)
$\Delta PROPSOLD_{t\text{-}1 \text{ to } t\text{-}4}$	1.613	-4.577**	-1.789***	-1.558*
	(0.199)	(0.045)	(0.000)	(0.054)
$\Delta DRES_{t\text{-}1 \text{ to } t\text{-}4}$	0.076**	-0.167**	-0.001	-0.347***
	(0.049)	(0.029)	(0.585)	(0.006)
Adjusted R^2	0.14	0.50	0.23	0.07

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity, price return, and investor sentiment measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability, market liquidity, and investor sentiment within the VAR system. Summed coefficients and p-values from a joint significance test are reported for each endogenous variable. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. PROPSOLD is the percentage of properties sold from the NCREIF NPI index. TBIRET is the natural log of the quarterly percentage change in the aggregate TBI price index. DRES is a direct survey measure of investor sentiment for the commercial real estate market obtained from the Real Estate Research Corporation's quarterly Real Estate Report. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), and the aggregate capitalization rate for commercial properties (CAPRT). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 3-11. Credit availability and investor sentiment using an indirect sentiment measure.

End. Variables	TBIRET	ΔTIGHTEN	ΔPROPSOLD	ΔINDRES
$TBIRET_{t\text{-}1 \text{ to } t\text{-}4}$	0.122***	-1.538***	-0.011	0.038
	(0.005)	(0.006)	(0.824)	(0.622)
$\Delta TIGHTEN_{t\text{-}1 \text{ to } t\text{-}4}$	-0.249***	-0.902***	-0.076*	-2.698
	(0.010)	(0.001)	(0.064)	(0.376)
$\Delta PROPSOLD_{t\text{-}1 \text{ to } t\text{-}4}$	2.006	0.100	-2.285***	-79.151**
	(0.647)	(0.118)	(0.000)	(0.033)
$\Delta INDRES_{t\text{-}1 \text{ to } t\text{-}4}$	0.020***	-0.085*	0.007	0.159***
	(0.000)	(0.087)	(0.228)	(0.000)
Adjusted R^2	0.35	0.56	0.29	0.06

This table presents results obtained from estimating unrestricted vector autoregressive (VAR) models with credit availability, market liquidity, price return, and investor sentiment measures specified as endogenous variables. The lag-length of the VAR is chosen by looking at the AIC, SBIC, and the likelihood ratio for various choices of p with four lags providing the best fit. Augmented Dickey Fuller tests suggest the use of changes in credit availability, market liquidity, and investor sentiment within the VAR system. Summed coefficients and p-values from a joint significance test are reported for each endogenous variable. TIGHTEN, is the net percentage of loan officers reporting a tightening of lending standards on commercial real estate loans in the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices. PROPSOLD is the percentage of properties sold from the NCREIF NPI index. TBIRET is the natural log of the quarterly percentage change in the aggregate TBI price index. INDRES is an indirect measure of investor sentiment for the commercial real estate market constructed from a number of sentiment proxies. Control variables include the yield on three-month U.S. Treasury securities (TBILL), the slope of the Treasury term structure of interest rates (TERMSPREAD), the spread between yields on BAA rated and AAA rated corporate bonds (DEFSPREAD), inflation (INFLA), the Fama-French factors: MKT, SMB, HML, augmented by momentum (UMD), and the aggregate capitalization rate for commercial properties (CAPRT). The sample period spans 1992:Q2 to 2009:Q4. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

CHAPTER 4
VOLUNTARY DISCLOSURE, INVESTOR SENTIMENT, AND RETURN COMOVEMENT

The decisions of major firms such as Coca-Cola®, PepsiCo, Berkshire Hathaway, and AT&T™ to reduce or eliminate practices of providing voluntary earnings guidance to its investors created much of a stir on Wall Street over the past decade. Historically, investors relied on these voluntary disclosures as an opportunity to examine a firm's current earning environment and its potential for future growth. However, there has been significant controversy as to whether the use of such announcements is in fact beneficial to shareholder wealth. On one hand, proponents for voluntary disclosure believe that management issued earnings guidance increases firm transparency and provides investors with a better understanding of a company's future profitability. On the other hand, critics believe that earnings guidance allows management to mislead investors in an attempt to facilitate higher asset valuations, particularly at times when investors are optimistic.

This paper adds to the growing debate on whether the strategic disclosure of earnings guidance by firm management caters to misguided investor beliefs. Several recent empirical studies have examined the effects of strategic disclosure on the time-series behavior of stock returns (Goto, Watanabe, Xu, 2009; Jiang, Xu, and Yao, 2009; Haggard Martin, and Pereira, 2008). Moreover, a few studies have begun to investigate the relation between voluntary disclosure practices and investor sentiment (Bergman and Roychowdhury, 2008; Seybert and Yang, 2011; Brown et al., 2011). While most of these studies have identified voluntary disclosure as a means for reducing information asymmetry, correcting overvaluation, and improving stock price informativeness, very few have provided evidence that managers issue earnings guidance to take advantage of misguided investor beliefs. Most prior studies have been limited by the fact that they have chosen to either aggregate the number of disclosures over a

particular period (disclosure frequency) or examine the disclosure over extremely short event horizons (event study). In doing so, the literature fails to address the influence that selective disclosure has on longer term asset price movements. Using a return comovement approach, I am able to provide new evidence contrary to these previous findings and consistent with managers catering their disclosures to take advantage of sentiment-induced mispricing.

The main contribution of this analysis focuses on determining whether firm management strategically issues voluntary earnings guidance in order to take advantage of misguided investor beliefs, particularly during periods of high investor optimism, and whether such disclosures have a significant impact on future asset price movements. In particular, I attempt to answer the following research question. Do firms that strategically disclose during high sentiment periods increase their comovement with stocks that are highly sensitive to shifts in investor sentiment (i.e., those firms that experience significant increases in their stock prices when investor sentiment rises) following the announcement? If firm managers strategically issue voluntary earnings guidance that is consistent with misguided investor beliefs, following the disclosure event one would expect these stocks to covary more with firms that are most sensitive to changes in investor sentiment and less with market fundamentals. As a byproduct of this analysis, I also provide evidence that adds to the literature on the determinants of return comovement. In particular, I provide further empirical support for the sentiment-based theory originally examined by Barberis, Shleifer, and Wurgler (2005).

I test my main hypothesis using a two-step approach. I begin by identifying those firms that are the most likely to strategically provide earnings guidance in order to take advantage of sentiment-induced beliefs. Because voluntary disclosure may be “sticky” I focus on voluntary earnings guidance provided by two subsets of disclosing firms: a “limited disclosure” sample

(LD), defined as those firms that have not provided voluntary earnings guidance in the 12 months prior to the event, and an "isolated disclosure" sample (ID), defined as those firms that disclose during only one year of my sample period and do not disclose in future years. I hypothesize that these firms are the most likely to strategically disclose since they do not have a history of repeat disclosures. The sample period of this study spans January 1998 to December 2008.

To identify whether company issued guidance impacts future asset price movements, I examine shifts in return comovement around the disclosure event. In particular, I utilize bivariate and multivariate regressions similar to Barberis, Shleifer, and Wurgler (2005) and Green and Hwang (2009). I estimate regressions for each firm using daily returns over the 12-month period ending one month prior to the disclosure and the 12-month period staring one month after the disclosure. The sentiment portfolio is constructed using a sentiment-beta approach similar to Glushkov (2006).

For both the LD and ID samples, I find that firms issuing voluntary earnings guidance during high sentiment periods experience a significant increase in return comovement with the sentiment portfolio and a significant decrease with market fundamentals following the disclosure event. Prior to the disclosure event, these firms exhibit negative or zero comovement with sentiment sensitive stocks. However, subsequent to the disclosure, disclosing firms experience significant positive comovement with the sentiment portfolio. This is consistent with managers issuing earnings guidance to take advantage of misguided investor beliefs during times of investor confidence. Furthermore, I find evidence that this effect is concentrated around the issuance of neutral earnings guidance, which by nature contains no new information about a

stock's fundamental value. This additional result supports the sentiment-based theory of comovement.

Background Literature

Several empirical studies have emerged examining how strategic disclosure of information affects the properties of time-series returns. Goto, Watanabe, and Xu (2009) document significant shifts in the properties of stock returns for firms that undergo changes in disclosure environments, focusing on firms that choose to cross-list a security on a foreign exchange. Jiang, Xu, and Yao (2009) analyze how the quality of information disclosures impact idiosyncratic volatility. These papers build off of a well established theoretical literature examining managers' incentives to either disclose or withhold information from their investors. This branch of literature has evolved considerably from the full disclosure theories of Grossman and Hart (1980) and Grossman (1981). Verrechia (1983) and Dye (1985) were the first to develop theoretical models for understanding a manager's incentives to cater their disclosure decisions based on the perceived cost of providing information. Subsequent work has focused on identifying the source of this cost. One aspect that has received increased attention is how the sophistication of investors and their ability (or inability) to interpret information affects the decision to disclose and the timing of the disclosure (Dye, 1998; Fishman and Hagerty, 2003).

One possibility is that firms cater their disclosure policies to take advantage of misguided investor beliefs at times when less sophisticated traders are likely to be the marginal investor. Delong, Shleifer, Summers and Waldman (1990) develop a theoretical model in which "noise traders," or less sophisticated investors, make portfolio allocations based upon misguided beliefs. Subsequent research defines these misguided beliefs about future cash flows and / or investment risks as investor sentiment (Baker and Wurgler 2006, 2007). Therefore, when investor sentiment

is high, managers may utilize this opportunity to issue earnings guidance in an attempt to take advantage of investor optimism and higher asset valuations.

Several recent empirical studies have begun to examine whether firms cater their voluntary disclosure decisions to the level of investor sentiment and how this impacts asset prices. Brown et al. (2011) find that a firm's propensity to disclose short-horizon adjusted (pro forma) earnings metrics increases with the level of sentiment. Furthermore, the authors provide evidence that managers tend to provide more favorable earnings metrics when investor sentiment increases. This study is limited by the fact that the authors focus only on short-horizon guidance and fail to examine any asset pricing implications of these disclosures. Bergman and Roychowdhury (2008) find that during high sentiment periods, managers reduce the frequency of their long-horizon earnings guidance in an attempt to "ride the wave" of investor optimism. However, this study fails to address the implications of those disclosures that are in fact made during these high sentiment periods. Seybert and Yang (2011) examine these disclosures more closely, focusing upon stock price movements in the days immediately surrounding the event. The authors provide evidence that earnings guidance aids in resolving sentiment-driven overvaluation over short event windows. Because the authors focus on both short and long-horizon guidance, as well as include all disclosures in their sample period, they overlook the events that are most likely designed to take advantage of investor sentiment's misguided beliefs. In addition, by examining returns over such a short-horizon, the authors are unable to document changes in the patterns of asset price movements over time.

Another way to identify changes in asset price movements around a corporate event is to test whether there is a significant shift in return comovement with a particular portfolio of stocks (e.g. stocks in the same industry, size deciles, index, etc.) following the event (Barberis, Shleifer,

and Wurgler, 2005; Greenwood, 2008; Kumar and Lee, 2006; Green and Hwang, 2009; Goto, Watanabe, and Xu, 2009). Of particular interest is the work of Barberis, Shleifer, and Wurgler (2005) who distinguish between two theories that attempt to explain why asset values move together over time: the fundamental- and sentiment-based theories of comovement. According to the fundamental-based theory, in a frictionless market consisting of rational investors, any comovement in returns is due to comovement in the asset's fundamentals. The sentiment-based theory, on the other hand, posits that the comovement in returns can be delinked from fundamentals in markets with frictions or those that consist of irrational investors.[1]

Haggard, Martin, and Pereira (2008) are the first to utilize voluntary disclosure as a criterion for return comovement. The authors examine whether firms with more forthcoming disclosure policies, based upon rankings of disclosure quality, covary more or less with market and industry returns. However, they do not analyze return comovement around specific disclosure events nor do they explicitly test the theory of sentiment-based return comovement.

This study is the first to utilize voluntary disclosure events to examine sentiment-based return comovement. Overall, I bridge the gap between the voluntary disclosure, investor sentiment and return comovement literature by examining whether strategically issued earnings guidance increases return comovement amongst firms that disclose and those firms that are most sensitive to changes in investor sentiment. I provide new evidence, contrary to Seybert and Yang (2011), supporting the hypothesis that strategically issued earnings guidance contributes to sentiment-induced mispricing.

[1] Veldkamp (2006) and Jin and Myers (2006) develop similar theories regarding information-based comovement within a rational expectations framework, where the revelation of new information takes the place of sentiment.

Data and Descriptive Statistics

Voluntary Disclosure

Since there is no regulation governing its issuance, management issued earnings guidance represents a voluntary form of information disclosure. At any point in time, firm management may decide to issue a press release or conduct an interview to provide investors with information regarding whether a firm expects to meet, beat, or fall short of analyst earnings estimates. These disclosures may be disseminated in the form of a specific numerical value, a range of estimates, or even a text statement. Since the scope of this study focuses primarily on identifying the date on which a voluntary disclosure is made, rather than point estimates of the earnings guidance themselves, I rely upon the Thomson First Call Company Issued Guidance (CIG) database as my source of voluntary disclosure data.

The CIG database contains management issued earnings guidance dating as far back as 1994. However, prior literature has documented significant shortcomings of this database in the early years of its existence, particularly its inability to capture all issuances of earnings guidance. Since First Call originally was created as a proprietary provider of sell-side analyst research, the collection of management issued earnings guidance was not its primary focus. Therefore, it is possible that this database initially suffered from significant sample selection bias, only capturing company issued earnings guidance for those firms with analyst coverage (Chuk, Matsumoto and Miller, 2009). However, Anilowski, Feng and Skinner (2007) document a significant expansion in First Call's coverage beginning in 1998, when they began to collect company issued earnings guidance in a more systematic fashion. In order to mitigate sample selection bias, the sample period begins in January of 1998 and runs through December 2008.

Bergman and Roychowdhury (2008) suggest that strategic disclosure is likely to be concentrated in long-horizon earnings guidance. The authors argue that managers are more likely

to be able to maintain optimistic earnings valuations in their long-horizon disclosures rather than their short-term guidance since they do not face the same short-run incentives to meet analyst estimates regarding imminent earnings announcements. Therefore, I focus specifically on long-horizon earnings guidance. Following Bergman and Roychowdhury (2008), I classify management forecasts that were issued more than 90 days before the estimate period end date as long-horizon earnings guidance.

Prior research documents that earnings guidance practices may be "sticky." In other words, if a firm initiates a disclosure policy, it may decide to continue to disclose from year to year or from period to period within a year. Most studies that have examined the role of voluntary disclosure in asset pricing have chosen to either aggregate the disclosures over a particular period (disclosure frequency) or examine the disclosure over short horizons (event study). In doing so, the literature fails to address the influence that selective disclosure has on longer term asset price movements.

Rather than focus on the frequency or incremental impact of each disclosure, I attempt to identify situations in which firms strategically disclose to take advantage of misguided investor beliefs. Prior research has shown that follow-up disclosures will typically walk-up or walk-down the initial guidance estimate (Bergman and Roychowdhury, 2008), suggesting that the incremental value of subsequent guidance is of secondary importance. In addition, the initial voluntary disclosure is an attention grabbing event that may ultimately attract investors to the stock (Barber and Odean, 2008). Therefore, I begin by collecting the first long-horizon disclosure in a firm's fiscal year for all firms in the CIG database.[2] I then further partition the

[2] I exclude real estate investment trusts (REITs) from my analysis for several reasons including the tendency of analysts to focus on funds from operations (FFO) estimates rather than earnings (EPS) for these firms, as well as empirical evidence that REIT returns appear to respond to real estate market sentiment, rather than stock market sentiment, as reported in my first study.

data into two groups for my main analysis. The first group, which I refer to as the "limited disclosure" (LD) sample, consists of firms that have not provided voluntary earnings guidance in the 12 months prior to the event.[3] The second group, which I refer to as the "isolated disclosure" (ID) sample, consists of firms that disclose during only one year of the sample period and do not disclose in future years. To address the potential complication of a look-ahead bias in the ID sample, I also examine the first time that a firm discloses, even if they do disclose again, in a series of robustness checks.

Sentiment Portfolio

Baker and Wurgler (2006, 2007) and Glushkov (2006) empirically examine whether certain stocks are more sensitive to sentiment by testing whether their prices co-move with an index of sentiment changes. In other words, a stock with a positive sentiment beta will experience a contemporaneous increase in price when investor sentiment increases. To identify firms that are highly sensitive to changes in investor sentiment, I utilize a sentiment beta approach similar to Glushkov (2006). In particular, I estimate an OLS regression of monthly stock returns on changes in investor sentiment and a series of fundamental control variables. The specification is as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_i^{BW}\Delta\mathrm{BW_t} + \beta_i^{MKT}\mathrm{MKT_t} + \beta_i^{SMB}\mathrm{SMB_t} + \beta_i^{HML}\mathrm{HML_t} + \beta_i^{MOM}\mathrm{MOM_t} + \beta_i^{LIQ}\mathrm{LIQ_t} + \varepsilon_{i,t} \quad (4\text{-}1)$$

where $R_{i,t}$ is the excess return of stock i at time t, ΔBW_t is the change in Baker and Wurgler's (2006, 2007) sentiment index[4], MKT_t is the excess return on the value-weighted market portfolio, SMB_t is the return on the small-minus-big size portfolio, HML_t is the return on the

[3] Christensen et al. (2011) utilize a more restrictive qualification criterion for what they identify as "occasional guiders." In robustness checks, I restrict the sample in a similar way to include only those firms that have not provided guidance in the 2 years prior to the event. Results are stronger in terms of the magnitude and precision of the coefficient estimates in the more restrictive case.

[4] I obtain the investor sentiment index for the general stock market from Jeffrey Wurgler's website and update the data through 2008.

high-minus-low book-to-market portfolio (Fama and French 1993, 1996), MOM_t is the return on the momentum portfolio (Carhart, 1997), and LIQ_t is Pastor and Stambaugh's (2006) liquidity factor.

Equation (4-1) is estimated using a five year (60 month) rolling window to obtain β_i^{BW} for each stock in the CRSP database. I start with monthly return data from January 1993, since the first observation in the voluntary disclosure database is from January 1998, and roll forward one month at a time until I have estimates for all months in the sample period. For each month in the sample period, I then construct a value-weighted portfolio consisting of those firms that exhibit a positive and statistically significant (at the 5% level) sentiment beta over the five year estimation period. This allows for a rebalancing of the sentiment portfolio each month based on which firms are most sensitive to changes in investor sentiment. The median number of firms included in the sentiment portfolio is approximately 170. The time series average sentiment beta for firms included in the sentiment portfolio is 0.07

Return and Control Variable Data Sources.

I obtain daily return data from the University of Chicago's Center for Research in Security Prices (CRSP). For the voluntary disclosure sample, I require firms have 12 months of daily return data available in the CRSP database prior to the event date. As a measure of market fundamentals I utilize the excess return on the value-weighted CRSP market portfolio (MKT). To control for return comovement that may be related to firm characteristics other than their exposure to sentiment and the market, I construct value-weighted indices related to size and industry classifications. For size portfolios, I categorize firms into size deciles based on market capitalization breakpoints at the end of each month. For industry portfolios, I utilize the Fama

and French 49 industry classifications. Size breakpoints and industry classifications are obtained from Kenneth French's website.

Descriptive Statistics

Table 4-1 reports descriptive statistics regarding the frequency of long-horizon disclosures by year for all firms in the CIG database, the LD sample, and the ID samples. Focusing on the first long-horizon disclosure in a fiscal year for all firms that provide voluntary disclosure, I begin with a sample of 11,024 firm observations over the eleven year sample period. The top panel of Table 4-1 indicates that the median number of long-horizon forecasts for all disclosing firms was a single disclosure prior to 2001. However, after 2001 there was a considerable increase in the frequency of disclosure for each firm within a particular year as well as the number of firms choosing to voluntarily disclose. This is consistent with Regulation Fair Disclosure (Reg. FD) encouraging firms to be more forthcoming with their disclosure policy beginning in late 2000. After 2000, the number of firms disclosing appears to remain fairly consistent, which may indicate that once firms begin their disclosure policy, they continue to provide guidance in the next year.

When I focus on firms that have not disclosed in the previous year (LD), as reported in the middle panel of Table 4-1, disclosure stickiness becomes less of an issue. This removes firms that are consistently providing earnings guidance from year to year and therefore places the focus on those firms that are more likely to be strategically varying their disclosure of earnings guidance. After applying this filter to the data, I am left with 3,420 firm observations. The average frequency of disclosure within year for these firms is less than the full disclosure sample, which eases concerns about isolating the first disclosure in a particular year as the event date for this subset of firms. When I compare the number of firms in the limited disclosure sample to all firms in the CIG database, the prevalence of repeat disclosure in the full sample becomes clear.

For example, if I compare the number of firms disclosing in year 2000 in the LD sample to those in all firms in the CIG database, 289 of the 617 firms that provided long-horizon earnings guidance did so in the previous year as well.

The bottom panel of Table 4-1 reports descriptive statistics for the ID sample. By including just those firms that disclose during only one year of the sample period and do not disclose in future years, I am left with 1,003 firm observations over the eleven year sample period. Throughout most of the sample period, the median number of long-horizon forecasts for these firms is a single disclosure within a year. Focusing on these firms is appealing for this study's empirical test as they appear to be the most likely to strategically select the timeliness of their disclosures. If they haven't disclosed before and do not disclose again, then the decision to disclose may be linked to taking advantage of when it is most advantageous for them to do so.

Prior research indicates that the level of investor sentiment is a key determinant of the timeliness of these disclosures. Therefore, it is important to understand how these disclosures are concentrated in high sentiment versus low sentiment periods. Panels A and B of Figure 4-1 display Baker and Wurgler's (2006, 2007) sentiment index (BWSENT) and the number of firms providing voluntary earnings guidance for the LD and ID samples, respectively. In both Panel A and Panel B, the number of firms that are disclosing is considerably higher when sentiment is high and decreases as investors become less optimistic. The contemporaneous correlation between the number of firms disclosing and movements in the sentiment index over the sample period are positive and significant for both the limited disclosure (0.17) and isolated disclosure (0.20) samples. This suggests that firms may provide voluntary earnings guidance when sentiment is high in order to take advantage of misguided investor beliefs. It is interesting to note that during the most significant decrease in sentiment, which occurred with the bursting off the

technology bubble in mid 2001, there are zero firms initiating new earnings guidance for their fiscal year. This suggests that firms may be more likely to strategically time their first voluntary disclosures to take advantage of increasing investor optimism.

Tables 4-2, 4-3, and 4-4 report descriptive statistics regarding industry, size, and return characteristics, respectively, for each set of disclosure firms as well as the sentiment portfolio. Table 4-2 documents the percentage of firms in each industry classification. For ease of presentation, I only report the top ten industry distributions from the Fama-French 49 industry categories. Baker and Wurgler (2006, 2007) suggest that small growth-oriented firms are highly susceptible to sentiment induced mispricing. Consistent with this hypothesis, firms in the sentiment portfolio are concentrated in growth-oriented industries such as Drugs (Pharmaceuticals), Chips, and Telecom. Firms that provided earnings guidance, on the other hand, are generally concentrated in value-oriented industries such as Utilities, Retail, and Business Services. This suggests that ex ante these firms would be less likely to be influenced by investor sentiment. One exception is the overlap observed in the software sector, where the divide between sentiment and disclosure firms is less prominent. This suggests that controlling for industry comovement will also be important in the multivariate specifications.

Table 4-3 reports the percentage of firms in each size decile. Consistent with Baker and Wurgler's (2006, 2007) hypothesis, the sentiment portfolio consists of a significant proportion of small stocks. In fact, 49% of the stocks in the sentiment portfolio are from the smallest size decile. In general, firms providing voluntary guidance appear to be more evenly distributed across size deciles. However, it is worth noting that the ID sample exhibits some similarities to the composition of the sentiment portfolio as it too includes a high proportion of firms from the

smallest size decile. Therefore, it will also be necessary to control for size-based comovement in multivariate regressions in order to isolate the sentiment effect.

While my primary regression specifications utilize individual firm stock returns as dependent variables, I construct aggregate return indices for each of the disclosure groups as well as the sentiment portfolio using daily data over the full sample period in order to provide some insight into the general characteristics of these portfolio returns. I report summary statistics for each of set of daily returns in Table 4-4. On average, the returns on the sentiment portfolio are higher and more volatile than those of firms that voluntarily disclose. This is consistent with Baker and Wurgler's (2006, 2007) predictions that high volatility stocks are likely to be most sensitive to changes in sentiment. This is also consistent with the premise that disclosing firms are more transparent and therefore have lower price volatility.

Empirical Methodology

Bivariate Regression Approach

In an attempt to distinguish between traditional and sentiment-based return comovement, Barberis, Shleifer and Wurgler (2005) are the first to utilize a bivariate regression approach to test whether return comovement shifts as firms are added to or removed from the S&P 500. In support of the sentiment-based view of comovement, the authors find that firms will covary more with S&P index stocks and less with non-S&P stocks after inclusion in the index, even if no new fundamental information about the firm has been revealed. Green and Hwang (2009) utilize a similar bivariate regression approach that includes high and low price portfolios to test whether firms experience a shift in return comovement around a stock split event. If investors categorize stocks based on price, the stock will covary more with the low price index and less with the high price index following the split.

I utilize a similar approach to identify whether firms experience a shift in return comovement around a voluntary disclosure event, except I focus on whether firms increase their comovement with the sentiment portfolio following the disclosure. If firm managers strategically issue voluntary earnings guidance that is consistent with misguided investor beliefs, following the disclosure event one would expect these stocks to covary more with stocks that are most sensitive to investor sentiment and less with the market portfolio, particularly during periods of high sentiment. This return comovement approach has the ability to not only capture the short run momentum created around the disclosure event, but also the long-run reversal that these stocks may experience in subsequent months. I estimate the following bivariate regression separately before and after the disclosure for each firm in both the LD and ID samples:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \varepsilon_{i,t} \tag{4-2}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the sentiment portfolio and $MKT_{i,t}$ is the excess return on the value-weighted market portfolio. To avoid spurious effects, I remove the contribution of the disclosure stock from the independent variables where appropriate. I estimate the regression using daily returns. The pre-event regression is run over the 12-month period ending one month prior to the disclosure and the post-event regression is run over the 12-month period staring one month after the disclosure. I report results for disclosures made over the entire sample period and then disaggregate disclosures into periods in which sentiment is positive (high sentiment) and periods in which sentiment is negative (low sentiment) to isolate the sentiment effect.

Multivariate Regressions

To control for other fundamental firm characteristics that may be driving return comovement around the disclosure event, I modify Equation 4-2 to include size and industry

portfolios. I estimate the following multivariate regression separately before and after the disclosure for both subsets of firms in the sample:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t} \quad (4\text{-}3)$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification).

The inclusion of industry and size portfolios controls for other potential causes of fundamentals-induced return comovement. Barberis, Shleifer and Wurgler (2005) suggest that investors may categorize assets according to size or industry characteristics, thereby causing firm valuations within these categories to move together. Furthermore, firms in certain industries may share common fundamental information concerning cash flows. Therefore, comovement may be driven by industry-level news outside of the disclosure. Similarly, firm size will be highly correlated with analyst following, liquidity, and institutional ownership, all of which may have an impact on how information is incorporated into prices. Finally, Baker and Wurgler (2006, 2007) hypothesize that sentiment's impact is likely to be concentrated in small growth firms since these firms are generally more difficult to value and more likely to be speculative stocks. To ensure that I am not just capturing small size and growth-oriented comovement with the sentiment portfolio, the inclusion of size and industry controls helps further isolate sentiment's role around the disclosure event.

Empirical Results

Bivariate Regressions

Table 4-5 provides estimates of the bivariate regression model for the LD sample. The cross-sectional mean of the changes in the slope coefficients, $\Delta\beta^{SENT}$ and $\Delta\beta^{MKT}$, and their

p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. Focusing first on the full sample period results, I provide preliminary, although weak, evidence that firms experience a shift in comovement with the sentiment portfolio around voluntary disclosure events. The coefficient on $\Delta\beta^{SENT}$ is positive (0.0126) and marginally significant (p-value=0.094). This is consistent with firms increasing their comovement with the sentiment portfolio after the disclosure. If firms are covarying more with stocks that are highly sensitive to changes in sentiment following the disclosure, then one would expect these firms to be moving less with market fundamentals after the event as well. While the sign of the coefficient on $\Delta\beta^{MKT}$ is negative (-0.0176), as expected, the change is not statistically significant (p-value = 0.185).

By aggregating results across the full sample period, it is possible to miss the differential effect that voluntary guidance may have on asset price movements in high versus low sentiment periods. Recall, I hypothesize that firm managers are likely to strategically issue voluntary guidance during high sentiment periods in such a manner that caters to misguided investor beliefs. Therefore, one would expect a shift in return comovement with the sentiment portfolio to be concentrated around disclosures that occur in high sentiment periods. When results are disaggregated into high and low sentiment periods, I find this to be the case.

Focusing on the high sentiment period results, I provide stronger evidence that firms increase their return comovement with the sentiment portfolio after voluntarily issuing earnings guidance. Although not reported, it is important to note that in each high sentiment regression specification the coefficient on β^{SENT} for the 12 months prior to the event is either negative or statistically indistinguishable from zero. This is consistent with the belief that, in general, firms participating in voluntary disclosure practices are more transparent and therefore ex ante should

be less susceptible to sentiment induced mispricing. However, if firms are using guidance to strategically cater to misguided investor beliefs during high sentiment periods, one would expect these firms to covary more with the sentiment portfolio after the disclosure. The coefficient on $\Delta\beta^{SENT}$ for the high sentiment specification is positive (0.0188) and strongly significant (p-value=0.037), supporting the hypothesis that strategic disclosure caters towards misguided investor beliefs. Equally important, I document a negative ($\Delta\beta^{MKT}$ = -0.0530) and statistically significant shift (p-value = 0.001) in comovement away from the market portfolio after the event. The corresponding decrease in the coefficient on the market portfolio indicates that the shift in comovement is less likely to be driven by a change in fundamentals following the disclosure. These results are consistent with Barberis, Shleifer, and Wurgler's (2005) theory of sentiment-based comovement.

Moving to the low sentiment period results, I do not find evidence of a significant shift in comovement with the sentiment portfolio ($\Delta\beta^{SENT}$ = -0.0035, p-value = 0.797) after the disclosure, suggesting that the effect is in fact concentrated in high sentiment periods. It is interesting to note that in the low sentiment state, however, I observe a significant increase in comovement with the market portfolio, suggesting that disclosures communicate more about fundamentals during market declines. This is consistent with prior literature documenting the use of earnings guidance to provide warnings to investors, particularly during economic downturns (Kasznik and Lev, 1995; Soffer, Thiagarajan and Walther, 2000).

Table 4-6 provides estimates of the bivariate regression model for the ID sample. Recall, firms in the ID sample only appear in one year of the sample period, so these firms may be more likely to cater their earnings guidance to misguided investor beliefs during high sentiment periods. In the full sample period specifications, I find results similar to those using the LD

sample. I document a marginally significant (p-value = 0.094) positive ($\Delta\beta^{SENT}$ = 0.0341) shift in return comovement with the sentiment portfolio around the disclosure event. However, even in the full sample period, I document a corresponding negative ($\Delta\beta^{MKT}$ = -0.0901) and statistically significant shift (p-value = 0.012) in comovement away from the market portfolio after the event. Moving to the high sentiment period results, coefficient estimates grow stronger in both magnitude and statistical significance. Following the issuance of earnings guidance during a high sentiment period, these firms experience an increase in their comovement with the sentiment portfolio ($\Delta\beta^{SENT}$ = 0.0438, p-value = 0.068) and a decrease in comovement with the market portfolio ($\Delta\beta^{MKT}$ = -0.1321, p-value = 0.002). However, in low sentiment periods, I do not observe any significant shifts in comovement around the disclosure event. Taken together, these results suggest that providing voluntary earnings guidance during periods of high sentiment causes firms to increase their return comovement with sentiment sensitive stocks and delink their returns from market fundamentals.

Multivariate Regressions

To ease concerns that the observed shift in comovement with the sentiment portfolio subsequent to the disclosure event is due to a change in market fundamentals, I estimate multivariate regressions that include size and industry portfolios in addition to the sentiment and market portfolios. Table 4-7 presents results for the LD sample. What I am most interested in observing is whether the high sentiment period results remain robust to the inclusion of size and industry controls. Even after controlling for other potential sources of fundamental-based comovement, I continue to document a significant positive shift ($\Delta\beta^{SENT}$ = 0.0165, p-value = 0.065) in return comovement with the sentiment portfolio following the issuance of voluntary earnings guidance in high sentiment periods. I also continue to find firms delinking from the market portfolio following the disclosure, as the shift in return comovement is negative and

marginally significant ($\Delta\beta^{MKT}$ = -0.0491, p-value = 0.083). Results for the low sentiment period are similar to those from the bivariate regressions, though the previously documented shift in return comovement with the market portfolio has weakened with the inclusion of industry and size controls. This may suggest that market, industry, and size portfolios are capturing some common sources of fundamental based comovement.

Estimates from multivariate regressions using the ID sample are reported in Table 4-8. After controlling for industry and size based comovement, I continue to find that firm returns covary more with the sentiment portfolio ($\Delta\beta^{SENT}$ = 0.0558, p-value = 0.023) and less with fundamentals following the issuance of earnings guidance in high sentiment periods. The magnitude of the coefficients and the precision of the estimates on the sentiment portfolio in the ID sample are considerably larger than in the case of the LD firms. This provides additional support for my initial hypothesis that sentiment-based return comovement increases following a voluntary disclosure event, particularly when focusing on firms that are more likely to strategically provide earnings guidance during high sentiment periods. Similar to the LD sample, results from the full sample and low sentiment period estimations have weakened with the inclusion of industry and size controls.

Matched Sample Regressions

Bergman and Roychowdhury (2008) suggest that firms reduce their frequency of disclosure during high sentiment periods in order to “ride the wave” of high sentiment-induced valuations. This suggests that firms who do not disclose (i.e. those that just “ride the wave”) may be equally as likely to increase their comovement with the sentiment portfolio during high sentiment periods. If this is the case, then the observed shift in comovement may not be related to the disclosure event, but rather to the period of high sentiment in which the event occurs. In

order to address this alternative explanation, I construct a matched sample of non-disclosing firms using the ID firms as the base case.

Using the ID sample as the base case for this match is appealing for several reasons. First of all, in comparison to the LD sample, firms in the ID sample exhibit size and industry characteristics that are more closely related to the sentiment portfolio than to the full sample of disclosure firms (Tables 4-2 and 4-3). Second, some may argue that creating a matched sample of non-disclosure firms suffers from an inherent endogeneity problem in that firms who disclose may be fundamentally different from those that never provide guidance (Houston, Lev and Tucker, 2010). Since the ID firms are those firms that only disclose during one year of the sample period and never disclose again, I believe that using these firms as the base case for the matched sample minimizes the potential endogeneity issue.[5] Finally, based on previous results, ID firms appear to exhibit the most significant shift in return comovement around disclosure events. Therefore, if the comovement was being driven purely by the level of sentiment in these months rather than the disclosure event, matching based on these points in time would be most appealing.

For each firm that voluntarily issues earnings guidance in the ID sample, I select a control firm from the same industry and same size decile that does not disclose at any point during the sample period. For each matched stock, I run bivariate and multivariate regressions over the 12-month period ending one month prior to the month of the ID firm's disclosure and the 12-month period starting one month after the ID firm's disclosure.

[5] An alternative approach for creating a matched sample would be to identify firms that have disclosed in the past, but have ceased to continue their disclosure policy in high sentiment periods. However, Houston, Lev, and Tucker (2010) argue that the reason why firms cease guidance is directly tied to a firm's poor record of meeting or beating analyst expectations, not to market timing.

Table 4-9 and 4-10 report bivariate and multivariate results, respectively, for the matched sample. For the purpose of this test, I focus only on high sentiment period results. In both the bivariate and multivariate specifications, matched firms do not exhibit the same significant positive shift in return comovement with the sentiment portfolio nor a significant delinking from fundamentals as documented previously for those firms that do issue voluntary earnings guidance in these same high sentiment periods. This further supports the hypothesis that firms may provide voluntary earnings guidance to take advantage of misguided investor beliefs during periods of high investor sentiment.

Multivariate Regressions by Disclosure Type

One of the contributions of this study is new evidence I provide in support of sentiment-based theories of return comovement. Some may argue that I am unable to distinguish between traditional (fundamental) and sentiment-based comovement in these empirical tests due to the nature of voluntary earnings guidance. In other words, voluntary earnings guidance may inherently provide new information about a firm's fundamental value. Therefore, the shift in comovement between disclosing stocks and the sentiment portfolio may be related to some underlying change in the fundamentals of these stocks that is currently unaccounted for. In other words, the specifications may suffer from an omitted variable bias. Therefore, I design an additional test based on the type of disclosure that will provide further evidence supporting the sentiment-based theory.

One of the key distinctions between fundamental- and sentiment-based comovement depends upon how the revelation of new information, or lack thereof, impacts asset price movements. According to the fundamental view of return comovement, events that do not signal a change in a stock's fundamental value should not cause a significant shift in return

comovement following the event. However, in the sentiment-based view, shifts in return comovement may occur even if no new information regarding fundamentals is disseminated.

The CIG database includes a field (CIG Description Code) that categorizes company issued earnings guidance based on how it compares to the consensus analyst forecast at the time the guidance is made. If the earnings guidance is greater than the consensus analyst estimate, then this disclosure is classified as a positive earnings surprise. If the earnings guidance is less than the consensus analyst estimate, then this disclosure is classified as a negative earnings surprise. If the earnings guidance meets consensus analyst expectations, then it is classified as neutral or as meeting analyst expectations. While I am aware of the limitations in using these classifications, such as the significant loss of observations due to missing codes (NA) or erroneous classifications,[6] they provide sufficient information for an additional test of the underlying hypotheses.

Since I am interested in understanding the impact of voluntary earnings guidance in times of high sentiment, I focus on neutral earnings guidance and positive earnings surprises during these periods. If managers wish to cater to optimistic investor beliefs during periods of high sentiment, one would expect them to issue either guidance that is consistent with these misguided beliefs (neutral) or that expands upon investor optimism (positive surprises). The distinguishing feature between these two types of guidance is the information, or lack thereof, being conveyed. Managers who strategically provide neutral guidance that merely meets analyst expectations are not conveying any new information about a firm's fundamentals. However, if a manager issues a positive earnings surprise, then new information is being released. Therefore, if one observes a significant positive shift in return comovement with the sentiment portfolio

[6] Rees and Wynalda (2008) provide a thorough analysis of the main issues regarding CIG Description Code classifications.

following the issuance of neutral guidance, which by nature contains no new information, this would further support the sentiment-based theory of comovement.

Tables 4-11 and 4-12 report estimates from multivariate regressions disaggregated by CIG Description Code for the LD and ID samples, respectively. I report results only for high sentiment period specifications. Focusing first on the LD sample in Table 4-11, consistent with the sentiment-based theory, I find a shift in return comovement with the sentiment portfolio concentrated in firm disclosures that provide no new information about firm fundamentals. In particular, I document a significant increase in comovement with the sentiment portfolio ($\Delta\beta^{SENT}$ = 0.0224, p-value = 0.076) following the issuance of neutral earnings guidance. There is a corresponding delinking from market fundamentals ($\Delta\beta^{MKT}$ = -0.0652, p-value = 0.076) following the event as well. In contrast, I do not observe any change in comovement with the sentiment portfolio or market portfolio subsequent to a positive earnings surprise. This indicates that when information is communicated, these firms do not tend to comove more with those stocks that are highly sensitive to sentiment.

In Table 4-12, I observe even stronger results when considering return comovement around the issuance of neutral earnings guidance for firms in the ID sample. Consistent with the hypothesis that these firms are more likely to use disclosure to take advantage of optimistic investor beliefs, the change in β^{SENT} is over three times as large as the change reported in Table 4-11 and is statistically significant at the 5% level ($\Delta\beta^{SENT}$ = 0.0785, p-value = 0.043). Again, I find a corresponding decrease in comovement with the market portfolio ($\Delta\beta^{MKT}$ = -0.2084, p-value = 0.035) following the disclosure. Just as in the LD sample, I do not find any evidence of a shift in comovement when information is communicated through a positive earnings surprise.

Additional Robustness Checks

Two remaining issues that I address in further robustness checks involve the manner in which I construct the two main samples of firms that voluntarily provide earnings guidance. The LD sample consists of firms that have not provided voluntary earnings guidance in the 12 months prior to the event. This particular criterion was chosen in order to mitigate the well-documented issue of "sticky" voluntary disclosures. To be more consistent with Christensen et al.'s (2011) definition of "occasional guiders," I restrict the sample of firms in a similar way to their study and include only those firms that have not provided guidance over the 2 years prior to the event and then test whether results remain consistent using this alternate classification. Table 4-13 reports estimates from multivariate regressions using the restricted LD sample (LD2). Utilizing the LD2 sample, I find even stronger results than originally reported in Table 4-7. First of all, the increase in comovement with the sentiment portfolio and decrease in comovement with the market portfolio following the disclosure is not only strongly significant in the high sentiment period estimations, but also in the regressions that span the entire sample period. Furthermore, in the high sentiment results, the change in β^{SENT} is approximately one and a half times that of the original estimate using the LD sample and is significant at the 5% level ($\Delta\beta^{SENT}$ = 0.0245, p-value = 0.018). Overall, results using the LD2 sample are stronger than estimates originally reported in Table 4-7.

The second issue that is addressed centers on the construction of the ID sample. Recall, the ID sample consists of firms that disclose during only one year of the sample period and do not disclose in future years. The main concern with this group of firms is the possibility that this sample suffers from a look-ahead bias. Therefore, I utilize an alternative approach in which I identify only the first time a firm voluntarily provides earnings guidance over the entire sample period, regardless of whether they disclose again in the future. Table 4-14 reports estimates from

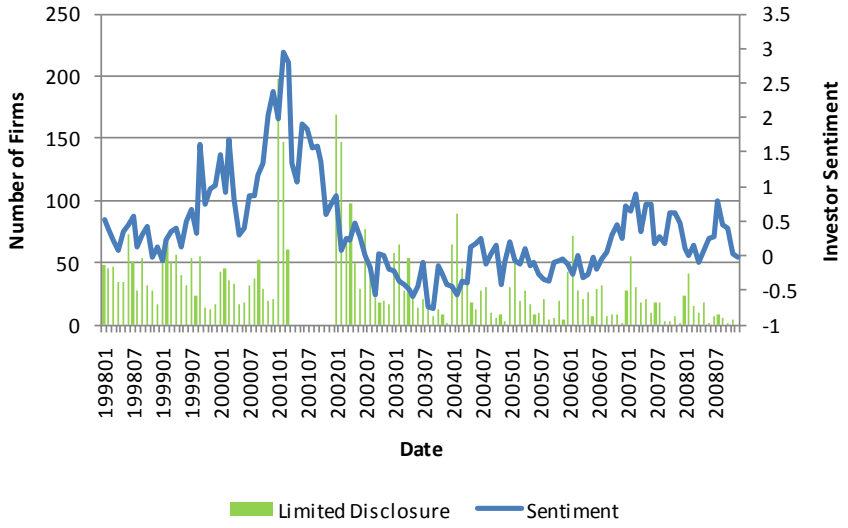
multivariate regressions using the first disclosure sample. I observe similar results to those reported in Table 4-8 using the ID sample. Therefore, I conclude that the issue of look-ahead bias is of secondary importance in affecting the empirical results of this study.

Summary and Conclusion

Whether the use of voluntary earnings guidance is in fact beneficial to firm shareholders is a debate that is far from over. While the initial motivation for providing guidance may have been to increase firm transparency and provide shareholders with a better understanding of a company's future profitability, the possibility remains that managers may use this opportunity to facilitate higher asset valuations, particularly at times when investors are overly optimistic. If firms issue earnings guidance that is consistent with misguided investor beliefs, voluntary disclosure may contribute to sentiment-induced mispricing, rather than aid in resolving sentiment-driven overvaluation.

This study adds to the growing literature that examines whether the strategic disclosure of earnings guidance caters to changes in investor expectations. The main contribution of this analysis focuses on determining whether firm management strategically issues voluntary earnings guidance in order to take advantage of misguided investor beliefs, particularly during periods of high investor optimism, and whether such disclosures have a significant impact on future asset price movements. In particular, I test whether firms that strategically disclose during high sentiment periods increase their comovement with stocks that are highly sensitive to shifts in investor sentiment (i.e. those firms that experience significant increases in their stock prices when investor sentiment rises) following the disclosure announcement. In so doing, this analysis is the first to study sentiment-based return comovement using voluntary disclosure events as a testing ground. Overall, I bridge the gap between the voluntary disclosure, investor sentiment and return comovement literatures.

Using bivariate and multivariate regression models, I provide new evidence, contrary to Seybert and Yang (2011), supporting the hypothesis that strategically issued earnings guidance contributes to sentiment-induced mispricing. In particular, I find that firms issuing voluntary earnings guidance during high sentiment periods experience a significant increase in return comovement with the sentiment portfolio and a significant decrease with market fundamentals following the disclosure event. Furthermore, I provide evidence that this effect is concentrated around the issuance of neutral earnings guidance, which by nature contains no new information about a stock's fundamental value. This result supports the sentiment-based theory of comovement as originally examined in Barberis, Shleifer, and Wurgler (2005).



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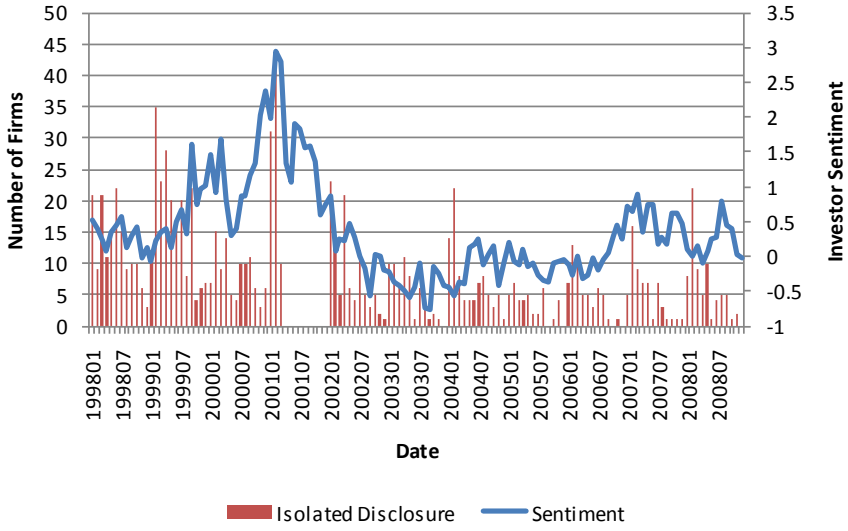


B

Figure 4-1. Investor sentiment and voluntary disclosure. A) This figure plots Baker and Wurgler's (2006, 2007) investor sentiment index and the number of firms providing voluntary earnings guidance for the "limited disclosure" (LD) sample. The LD sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. B) This figure plots Baker and Wurgler's (2006,2007) investor sentiment index and the number of firms providing voluntary earnings guidance for the "isolated disclosure" (ID) sample. The ID sample consists of those firms that disclose during only one year of the sample period. The sample period spans from January 1998 to December 2008.

Table 4-1. Descriptive statistics: voluntary disclosure.

	Year	Mean	Median	St Dev	Min	Max	N
	1998	1.583	1	1.157	1	15	489
	1999	1.788	1	1.511	1	24	676
	2000	1.893	1	1.452	1	12	617
	2001	2.501	2	2.017	1	25	1147
	2002	3.137	2	2.620	1	31	1150
All Firms	2003	3.209	3	2.579	1	33	1162
	2004	3.369	3	2.637	1	36	1274
	2005	3.523	3	2.469	1	24	1132
	2006	3.545	3	2.500	1	25	1195
	2007	3.415	3	2.276	1	24	1164
	2008	3.677	3	2.281	1	20	1018
	1998	1.621	1	1.017	1	7	449
	1999	1.726	1	1.387	1	16	442
	2000	1.668	1	1.076	1	8	328
	2001	2.718	2	2.238	1	25	365
	2002	2.900	2	2.238	1	17	680
Limited Disclosure (LD)	2003	2.327	2	1.990	1	16	260
	2004	2.118	2	1.603	1	13	289
	2005	2.122	2	1.432	1	9	139
	2006	2.163	2	1.488	1	9	208
	2007	2.149	2	1.372	1	7	148
	2008	2.596	2	2.022	1	18	104
	1998	1.461	1	0.913	1	7	152
	1999	1.518	1	0.947	1	7	199
	2000	1.390	1	0.709	1	5	100
	2001	2.071	2	1.438	1	8	84
	2002	1.970	1	1.609	1	12	101
Isolated Disclosure (ID)	2003	1.517	1	1.000	1	6	60
	2004	1.553	1	1.006	1	6	85
	2005	1.550	1	0.986	1	4	40
	2006	2.070	2	1.498	1	9	57
	2007	1.678	1	0.937	1	4	59
	2008	2.528	2	1.289	1	6	72

This table reports descriptive statistics regarding the frequency of disclosure for all firms in the Thomson First Call CIG database, the "limited disclosure" (LD) sample, and the "isolated disclosure" (ID) sample for each year of the sample period. The focus is on long-horizon earnings estimates defined as forecasts that were issued more than 90 days before the estimate period end date. Mean, median, standard deviation, minimum, maximum, and the number of firm observations for each year are reported. The sample period spans from January 1998 to December 2008.

Table 4-2. Industry classifications: voluntary disclosure and sentiment portfolios.

	Drugs	Oil	Software	Telecom	Chips	Util.	Bus. Services	Retail	Wholesale	Machine
Sent. Port	9.921	5.186	10.665	2.701	8.972	1.517	5.732	4.198	4.268	3.050
LD Firms	3.197	1.896	10.884	1.245	7.048	2.193	7.987	5.889	6.293	2.980
ID Firms	3.514	3.268	11.717	3.107	9.039	1.818	8.306	4.721	5.687	3.359
All CIG	3.251	1.489	9.554	1.104	5.885	3.083	7.434	8.311	5.802	3.939

This table reports descriptive statistics pertaining to the industry characteristics of firms in the sentiment portfolio, limited disclosure sample, isolated disclosure sample, and all firms in the Thomson First Call CIG database. A sentiment-beta approach similar to Glushkov (2006) is used to identify those firms that are most sensitive to changes in investor sentiment and a value-weighted portfolio is constructed for each month in the sample period. The specification is as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_i^{BW} \Delta \mathrm{BW_t} + \beta_i^{MKT} \mathrm{MKT_t} + \beta_i^{SMB} \mathrm{SMB_t} + \beta_i^{HML} \mathrm{HML_t} + \beta_i^{MOM} \mathrm{MOM_t} + \beta_i^{LIQ} \mathrm{LIQ_t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, BW_t is Baker and Wurgler's (2006, 2007)stock market sentiment index, MKT_t is the excess return on the value-weighted market portfolio, SMB_t is the return on the small-minus-big size portfolio, HML_t is the return on the high-minus-low book-to-market portfolio, MOM_t is the return on the momentum portfolio, and LIQ_t is the liquidity factor. The limited disclosure sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. The isolated disclosure sample consists of those firms that disclose during only one year of the sample period. Industry classifications are based upon Fama and French 49 industry classifications. Only the top ten industry distributions are reported. Industry classifications are obtained from Kenneth French's website. All statistics are reported in percentage form. The sample period spans from January 1998 to December 2008.

Table 4-3. Size classifications: voluntary disclosure and sentiment portfolios.

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Sent. Port	49.060	14.509	7.881	5.802	4.345	3.632	3.437	3.285	3.210	4.839
LD Firms	27.812	14.628	11.952	9.199	7.712	7.864	5.433	5.286	5.534	4.580
ID Firms	43.548	15.340	8.552	9.108	7.170	5.079	3.638	2.809	2.646	2.111
All CIG	21.410	13.524	11.533	9.465	8.825	8.519	6.454	6.654	7.013	6.601

This table reports descriptive statistics pertaining to the size characteristics of firms in the sentiment portfolio, limited disclosure sample, isolated disclosure sample, and all firms in the Thomson First Call CIG database. A sentiment-beta approach similar to Glushkov (2006) is used to identify those firms that are most sensitive to changes in investor sentiment and a value-weighted portfolio is constructed for each month in the sample period. The specification is as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_i^{BW} \Delta \mathrm{BW_t} + \beta_i^{MKT} \mathrm{MKT_t} + \beta_i^{SMB} \mathrm{SMB_t} + \beta_i^{HML} \mathrm{HML_t} + \beta_i^{MOM} \mathrm{MOM_t} + \beta_i^{LIQ} \mathrm{LIQ_t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, BW_t is Baker and Wurgler's (2006, 2007) stock market sentiment index, MKT_t is the excess return on the value-weighted market portfolio, SMB_t is the return on the small-minus-big size portfolio, HML_t is the return on the high-minus-low book-to-market portfolio, MOM_t is the return on the momentum portfolio, and LIQ_t is the liquidity factor. The limited disclosure sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. The isolated disclosure sample consists of those firms that disclose during only one year of the sample period. Size categories are deciles (from smallest to largest) based upon market capitalization breakpoints at the end of each month. Size breakpoints are obtained from Kenneth French's website. All statistics are reported in percentage form. The sample period spans from January 1998 to December 2008.

Table 4-4. Portfolio daily returns: voluntary disclosure and sentiment portfolios.

	Mean	Median	St Dev	Min	Max	Serial Correlation
Sent. Port	0.092	0.132	2.381	-11.289	21.885	-0.03
LD Firms	0.065	0.057	1.652	-12.651	10.884	0.01
ID Firms	0.053	0.008	2.125	-15.891	20.769	0.04
All CIG	0.062	0.049	1.630	-17.892	9.697	-0.01

This table reports descriptive statistics pertaining to the daily returns of value-weighted portfolios constructed for firms in the sentiment portfolio, limited disclosure sample, isolated disclosure sample, and all firms in the Thomson First Call CIG database for each month in the sample period. A sentiment-beta approach similar to Glushkov (2006) is used to identify those firms that are most sensitive to changes in investor sentiment and a value-weighted portfolio is constructed for each month in the sample period. The specification is as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_i^{BW}\Delta\mathrm{BW_t} + \beta_i^{MKT}\mathrm{MKT_t} + \beta_i^{SMB}\mathrm{SMB_t} + \beta_i^{HML}\mathrm{HML_t} + \beta_i^{MOM}\mathrm{MOM_t} + \beta_i^{LIQ}\mathrm{LIQ_t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, BW_t is Baker and Wurgler's (2006, 2007) stock market sentiment index, MKT_t is the excess return on the value-weighted market portfolio, SMB_t is the return on the small-minus-big size portfolio, HML_t is the return on the high-minus-low book-to-market portfolio, MOM_t is the return on the momentum portfolio, and LIQ_t is the liquidity factor. The limited disclosure sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. The isolated disclosure sample consists of those firms that disclose during only one year of the sample period. All statistics are reported in percentage form. Mean, median, standard deviation, minimum, maximum, and serial correlation are reported. The sample period spans from January 1998 to December 2008.

Table 4-5. Bivariate regression results: limited disclosure.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	ΔR^2	N
Full Sample Period	0.013*	-0.018	0.018	3420
	(0.094)	(0.185)	(0.000)	
High Sentiment	0.019**	-0.053***	0.026	2461
	(0.037)	(0.001)	(0.000)	
Low Sentiment	-0.003	0.073***	-0.002	959
	(0.797)	(0.003)	(0.526)	

This table presents results obtained from estimating bivariate regression models for the limited disclosure (LD) sample. The LD sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. The bivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio and $MKT_{i,t}$ is the excess return on the value-weighted market portfolio. Bivariate regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the disclosure and the 12-month period staring one month after the disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$ and $\Delta\beta^{MKT}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-6. Bivariate regression results: isolated disclosure.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	ΔR^2	N
Full Sample Period	0.034*	-0.090**	0.006	1003
	(0.094)	(0.012)	(0.082)	
High Sentiment	0.044*	-0.132***	0.006	752
	(0.068)	(0.002)	(0.121)	
Low Sentiment	0.005	0.036	0.005	251
	(0.898)	(0.573)	(0.431)	

This table presents results obtained from estimating bivariate regression models for the isolated disclosure (ID) sample. The ID sample consists of those firms that disclose during only one year of the sample period. The bivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio and $MKT_{i,t}$ is the excess return on the value-weighted market portfolio. Bivariate regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the disclosure and the 12-month period staring one month after the disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$ and $\Delta\beta^{MKT}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-7. Multivariate regression results: limited disclosure.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Full Sample Period	0.012*	-0.052**	0.031	0.023	0.020	3420
	(0.114)	(0.028)	(0.433)	(0.138)	(0.000)	
High Sentiment	0.016*	-0.049*	0.056	0.014	0.028	2461
	(0.065)	(0.083)	(0.303)	(0.454)	(0.000)	
Low Sentiment	0.001	-0.059	-0.032	0.049	-0.001	959
	(0.961)	(0.170)	(0.251)	(0.129)	(0.812)	

This table presents results obtained from estimating multivariate regression models for the limited disclosure (LD) sample. The LD sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where Ri,t is the excess return of stock i at time t, SENTi,t is the excess return on the value-weighted sentiment portfolio, MKTi,t is the excess return on the value-weighted market portfolio, SIZEi,t is the value-weighted size index return (using size deciles), and INDi,t is the value-weighted industry return (using the Fama and French 49-industry classification). Multivariate regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the disclosure and the 12-month period staring one month after the disclosure. The cross-sectional means of the changes in the slope coefficients, ΔβSENT, ΔβMKT, ΔβSIZE, and ΔβIND, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-8. Multivariate regression results: isolated disclosure.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Full Sample Period	0.048**	-0.046	-0.004	-0.059	0.003	1003
	(0.029)	(0.487)	(0.948)	(0.186)	(0.505)	
High Sentiment	0.056**	-0.062	-0.005	-0.056	0.003	752
	(0.023)	(0.441)	(0.944)	(0.247)	(0.528)	
Low Sentiment	0.025	0.002	0.000	-0.068	0.002	251
	(0.599)	(0.982)	(0.998)	(0.515)	(0.821)	

This table presents results obtained from estimating multivariate regression models for the isolated disclosure (ID) sample. The ID sample consists of those firms that disclose during only one year of the sample period. The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification). Multivariate regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the disclosure and the 12-month period staring one month after the disclosure. The cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$, $\Delta\beta^{MKT}$, $\Delta\beta^{SIZE}$, and $\Delta\beta^{IND}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-9. Bivariate regression results: matched sample.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	ΔR^2	N
Full Sample Period	0.002	-0.069	0.011***	1003
	(0.950)	(0.452)	(0.003)	
High Sentiment	0.018	-0.074	0.014***	752
	(0.647)	(0.217)	(0.001)	
Low Sentiment	-0.049	0.170*	0.002	251
	(0.451)	(0.082)	(0.783)	

This table presents results obtained from estimating a bivariate regression model for a matched sample for firms. For each firm that voluntarily issues earnings guidance in the isolated disclosure (ID) sample, I select a control firm from the same industry and same size decile that does not disclose at any point during the sample period. The bivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\,\mathrm{SENT}_{i,t} + \beta_i^{MKT}\,\mathrm{MKT}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio and $MKT_{i,t}$ is the excess return on the value-weighted market portfolio. Regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the ID firm's disclosure and the 12-month period staring one month after the ID firm's disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$ and $\Delta\beta^{MKT}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-10. Multivariate regression results: matched sample.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Full Sample Period	0.017	-0.039	-0.036	0.017	0.014	1003
	(0.441)	(0.649)	(0.354)	(0.810)	(0.002)	
High Sentiment	0.023	-0.130	-0.033	0.073	0.016	752
	(0.375)	(0.171)	(0.487)	(0.310)	(0.002)	
Low Sentiment	-0.002	0.255	-0.049	-0.167	0.006	251
	(0.952)	(0.200)	(0.474)	(0.366)	(0.492)	

This table presents results obtained from estimating a multivariate regression model for a matched sample of firms. For each firm that voluntarily issues earnings guidance in the isolated disclosure (ID) sample, I select a control firm from the same industry and same size decile that does not disclose at any point during the sample period. The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification). Regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the ID firm's disclosure and the 12-month period staring one month after the ID firm's disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$, $\Delta\beta^{MKT}$, $\Delta\beta^{SIZE}$, and $\Delta\beta^{IND}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-11. Multivariate regression results by disclosure type: limited disclosure.

Disclosure Type	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Neutral	0.022*	-0.065*	0.041	0.025	0.034	1169
	(0.076)	(0.076)	(0.318)	(0.269)	(0.000)	
Positive Surprise	-0.006	-0.066	0.044	0.028	0.070	348
	(0.782)	(0.324)	(0.377)	(0.539)	(0.000)	

This table presents results obtained from estimating multivariate regression models by disclosure type for the limited disclosure (LD) sample. The LD sample consists of those firms that have not provided voluntary earnings guidance in the 12 months prior to the disclosure event. Disclosures are classified using Thomson First Call's CIG Description Code variable. If the earnings guidance is greater than the consensus analyst estimate, then this disclosure is classified as a "positive surprise." If the earnings guidance meets consensus analyst expectations, then it is classified as "neutral." The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification). Regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the LD firm's disclosure and the 12-month period staring one month after the LD firm's disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$, $\Delta\beta^{MKT}$, $\Delta\beta^{SIZE}$, and $\Delta\beta^{IND}$, and their p-values only for high sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-12. Multivariate regression results by disclosure type: isolated disclosure.

Disclosure Type	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Neutral	0.078**	-0.208**	0.099	0.072	0.011	295
	(0.043)	(0.035)	(0.477)	(0.260)	(0.142)	
Positive Surprise	0.005	-0.082	0.096	-0.174	0.047	109
	(0.943)	(0.775)	(0.503)	(0.206)	(0.010)	

This table presents results obtained from estimating multivariate regression models by disclosure type for the isolated disclosure (ID) sample. The ID sample consists of those firms that disclose during only one year of the sample period. Disclosures are classified using Thomson First Call's CIG Description Code variable. If the earnings guidance is greater than the consensus analyst estimate, then this disclosure is classified as a "positive surprise." If the earnings guidance meets consensus analyst expectations, then it is classified as "neutral." The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification). Regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the ID firm's disclosure and the 12-month period staring one month after the ID firm's disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$, $\Delta\beta^{MKT}$, $\Delta\beta^{SIZE}$, and $\Delta\beta^{IND}$, and their p-values only for high sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-13. Multivariate regression results for robustness checks: restricted limited disclosure.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Full Sample Period	0.023**	-0.059**	0.024	0.016	0.020	2646
	(0.012)	(0.034)	(0.625)	(0.389)	(0.000)	
High Sentiment	0.024**	-0.074*	0.044	0.014	0.026	1977
	(0.018)	(0.057)	(0.492)	(0.507)	(0.000)	
Low Sentiment	0.017	-0.050	-0.037	0.023	0.002	669
	(0.353)	(0.350)	(0.299)	(0.577)	(0.644)	

This table presents results obtained from estimating multivariate regression models for the restricted limited disclosure sample (LD2). The LD2 sample consists of those firms that have not provided guidance over the two years prior to the disclosure event. The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification). Regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the firm's disclosure and the 12-month period staring one month after the firm's disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$, $\Delta\beta^{MKT}$, $\Delta\beta^{SIZE}$, and $\Delta\beta^{IND}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

Table 4-14. Multivariate regression results for robustness checks: first disclosure.

Period	$\Delta\beta^{SENT}$	$\Delta\beta^{MKT}$	$\Delta\beta^{SIZE}$	$\Delta\beta^{IND}$	ΔR^2	N
Full Sample Period	0.022**	-0.051*	-0.007	-0.001	0.012	2415
	(0.021)	(0.085)	(0.790)	(0.947)	(0.000)	
High Sentiment	0.027**	-0.048	0.002	-0.010	0.018	1877
	(0.014)	(0.154)	(0.944)	(0.632)	(0.000)	
Low Sentiment	0.007	-0.061	-0.038	0.031	-0.008	538
	(0.735)	(0.323)	(0.345)	(0.528)	(0.085)	

This table presents results obtained from estimating multivariate regression models for the first disclosure sample. The first disclosure sample keeps only the first time a firm voluntarily provides earnings guidance over the entire sample period, regardless of whether they disclose again in the future. The multivariate specification can be represented as follows:

$$R_{i,t} = \alpha_i + \beta_i^{SENT}\mathrm{SENT}_{i,t} + \beta_i^{MKT}\mathrm{MKT}_{i,t} + \beta_i^{SIZE}\mathrm{SIZE}_{i,t} + \beta_i^{IND}\mathrm{IND}_{i,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i at time t, $SENT_{i,t}$ is the excess return on the value-weighted sentiment portfolio, $MKT_{i,t}$ is the excess return on the value-weighted market portfolio, $SIZE_{i,t}$ is the value-weighted size index return (using size deciles), and $IND_{i,t}$ is the value-weighted industry return (using the Fama and French 49-industry classification). Regressions are estimated for each firm using daily returns over the 12-month period ending one month prior to the firm's disclosure and the 12-month period staring one month after the firm's disclosure. Cross-sectional means of the changes in the slope coefficients, $\Delta\beta^{SENT}$, $\Delta\beta^{MKT}$, $\Delta\beta^{SIZE}$, and $\Delta\beta^{IND}$, and their p-values over the full sample period, during high sentiment periods, and during low sentiment periods are reported. The sample period spans from January 1998 to December 2008. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

CHAPTER 5
CONCLUSION

Efficient financial markets assume that security prices represent fair valuations by rational investors, explicitly incorporate the perceived debt and equity financing costs of the marginal investor, and reflect all available public information. However, over the past decade, the rapid rise of asset prices in the technology sector and real estate market, liquidity crises such as those of Long Term Capital Management and Lehman Brothers, and the use of misleading information at the heart of accounting scandals such as those of Enron and WorldCom, have weakened support among economists for asset pricing models based on the assumptions of efficient markets, rational expectations, and costless arbitrage. In each scenario, factors outside of traditional fundamental determinants of value had a significant impact on asset price movements.

During periods of asset pricing booms, funds flow freely to speculative investors, thereby providing them with the means to bid asset prices above their fundamental value. As financial markets become less liquid in times of economic distress, investors are limited in their ability to enter the market and may even be forced to sell assets in order to meet outstanding funding requirements, thereby causing asset prices to decline below what market fundamentals dictate. When managers utilize information to mislead investors, this information may be incorporated into asset values even if other fundamental determinants of value remain unchanged. Put simply, asset prices are sensitive to market frictions and behavioral influences that may, at times, lead asset prices away from their fundamental value. Testing the impact of these factors and identifying the market conditions in which they matter most provides a significant contribution to the field of financial research.

In three studies, I examine the impact that behavioral factors, market frictions, and information dissemination have on asset price movements in both private and public markets. In

particular, I study the roles that investor sentiment, credit availability and voluntary disclosure of earnings guidance play in driving asset prices away from their fundamental values.

In my first study, I examine the differential impact of investor sentiment on both short- and long-run returns in public and private commercial real estate markets. Theory predicts that the illiquidity, information asymmetries, more limited price revelation, and inability to short-sell inherent in private markets may lead to prolonged periods of sentiment-induced mispricing. I find that investor sentiment plays a more persistent role in pushing asset prices away from their fundamental values in private markets because of the increased illiquidity and limits to arbitrage. This study is the first to directly investigate the relative importance of sentiment in public and private asset markets.

In my second study, I examine the relation between credit availability, market liquidity and asset price movements in both private and public commercial real estate markets. Given the relative illiquidity and significant use of leverage in acquisitions within commercial real estate markets, theory predicts that funding constraints are likely to play a significant role in asset price determination. I find asset values of highly leveraged assets, such as commercial real estate, to be sensitive to the availability of credit, even after controlling for other fundamental determinants of value. In addition, I provide evidence that assets trading in illiquid segments of the commercial real estate market are highly susceptible to a spiral effect, in which changes in asset prices lead to further changes in the availability of credit, thus magnifying the overall price impact of a funding shock. These results suggest that while leverage plays a significant role in determining credit market availability pricing effects, the underlying liquidity with which these assets trade is a key factor in determining the likelihood of a liquidity spiral, with lower liquidity creating the market setting for a spiral effect.

In my third study, I examine whether firm management strategically issues voluntary earnings guidance in order to take advantage of misguided investor beliefs, particularly during periods of high investor optimism, and whether such disclosures have a significant impact on future asset price movements. While the initial motivation for providing voluntary earnings guidance may have been to increase firm transparency and provide shareholders with a better understanding of a company's future profitability, the possibility remains that managers may use this opportunity to facilitate higher asset valuations, particularly at times when investors are overly optimistic. I find that firms issuing voluntary earnings guidance during periods of investor confidence covary more with firms that are most sensitive to changes in investor sentiment and less with market fundamentals following the disclosure event. Furthermore, I provide evidence that this effect is concentrated around the issuance of neutral earnings guidance, which by nature contains no new information about a stock's fundamental value. This result directly supports the sentiment-based theory of comovement.

Taken together, these three studies provide evidence that behavioral factors, such as investor sentiment, market frictions, such as a lack of liquidity or changes in the credit supply, and the strategic issuance of value-relevant information, such as the voluntary disclosure of earnings guidance, can have significant impacts on asset price movements. Furthermore, my results indicate that certain market conditions, such as significant limits to arbitrage, funding constraints in relatively illiquid markets, or periods of investor optimism may act as a catalyst for non-fundamental-based pricing effects.

APPENDIX
BOOTSTRAPPING WITH LONG HORIZON REGRESSIONS

Bootstrap Simulation Procedure

Inference based on asymptotic theory can be extremely misleading with small sample sizes, where many asymptotic tests may over-reject or under-reject the null hypothesis depending on the particular sample size. Several recent studies have utilized bootstrap simulation procedures to produce more accurate coefficient estimates and more reliable measures of inference within small sample settings. Instead of imposing a restrictive shape on the sampling distribution of desired parameter estimates, the bootstrap empirically estimates the sampling distribution from the original sample by sampling repeatedly with replacement from the actual data.

I follow the framework of the bootstrap simulation procedure described in Brown and Cliff (2005), but also incorporate several additional adjustments proposed in the more recent literature.[1] First, I begin by running long-horizon regressions as specified in Equation 2-2. The original OLS coefficient estimates on measures of investor sentiment are saved, as they will be utilized to calculate bias-adjusted coefficient estimates. The second step in the simulation procedure is to generate a pseudo return series under the null hypothesis that sentiment does not matter. I utilize the following vector autoregressive (VAR) model as the underlying data generating process of the pseudo return series:

$$\text{VAR(1) for } y_t = [r_t\ S_t\ z_t], \tag{A-1}$$

where r_t is the contemporaneous log return (i.e., the set of returns that was the basis for calculating the original future k-period return series), z_t is the set of contemporaneous control

[1] See also Menkhoff and Rebitzky (2008), Schmeling (2007), and Schmeling and Schrimpf (2008).

variables, and S_t is the measure of investor sentiment.[2] The beta coefficient on investor sentiment is set to zero in this case to ensure that the pseudo return series is generated under the null hypothesis that sentiment does not affect returns, and the constant in the constrained model is adjusted to restore the original mean. I save the predicted y-values and the residuals from the VAR specification.

Before proceeding, the residuals must first be adjusted to correct for a downward bias that results from the use of Least Squares in the VAR framework. Thus, each residual is multiplied by $(n/n\text{-}v)^{1/2}$, where n is the number of observations and v refers to the degrees of freedom of the VAR (MacKinnon, 2002). I then sample with replacement from these residuals to generate a new set of bootstrapped residuals.

This sampling process is repeated 10,100 times, with the first 100 samples of bootstrapped residuals being discarded to avoid any startup effects. I use the remaining residual datasets to create 10,000 bootstrapped dependent variables by adding the predicted y-value from the VAR to the new residual. From this pseudo return series, I create 10,000 new sets of k-period future returns. I then run long-horizon return regressions as specified in Equation 2-2, except in this case I use the new k-period future returns as the dependent variables. I save the beta coefficients from each of the regressions, yielding 10,000 betas for each of the return horizons. I then calculate the mean beta coefficient and the standard deviation of the estimated values of beta (bootstrap standard error) across the 10,000 simulations. These will be used to create a bias-adjusted beta coefficient and a new empirical distribution of t-statistics for inference.

MacKinnon and Smith (1998) demonstrate how bootstrap simulations can be utilized to generate more accurate beta coefficient estimates within finite sample settings. When the bias

[2] SBIC model-selection criteria indicates that a VAR (1) specification is appropriate.

function is not known analytically, the authors hypothesize that it can be estimated through the bootstrap simulation procedure as previously discussed. Assuming the bias is constant for a particular return horizon, the estimated bias can be calculated as follows:

$$\text{Estimated Bias} = \bar{\beta} - \hat{\beta}_{OLS}\,, \tag{A-2}$$

where $\hat{\beta}_{OLS}$ is the original OLS beta coefficient and $\bar{\beta}$ is the sample mean of the 10,000 simulated beta coefficients. Because the simulated samples are assumed to be drawn from the same model as the original data, the estimated bias function should converge to the actual bias function as the number of simulations approaches infinity. The adjusted beta coefficient can therefore be specified as:

$$\hat{\beta}_{adj} = 2\hat{\beta}_{OLS} - \bar{\beta}. \tag{A-3}$$

This is the mathematical equivalent of subtracting the estimated bias from the original OLS coefficient estimate. This bias-adjusted estimator has been used extensively in the bootstrap literature and has been shown to provide more reliable coefficient estimates in numerous simulation based studies.

The bootstrap procedure's primary application has been to develop more accurate measures for hypothesis testing and more appropriate confidence intervals for inference. In fact, the bootstrap procedure was originally proposed as an alternative method to compute standard errors (Efron, 1979). Prior literature has documented that Newey-West standard errors perform poorly in finite samples with overlapping observations. In particular, research has shown that standard errors calculated in this fashion suffer from a significant downward bias in small samples (Andrews, 1991). This implies that test statistics based on these estimated error terms are likely to result in false inferences. When asymptotic standard errors are unreliable, the

simplest alternative is to utilize the bootstrap standard error, which is calculated using the following specification:

$$se(\hat{\beta}) = \left(\frac{1}{B-1}\sum_{i=1}^{B}(\hat{\beta}_i - \bar{\beta})^2\right)^{\frac{1}{2}}, \tag{A-4}$$

where $\hat{\beta}_i$ is the estimated beta coefficient from iteration i of the simulation process, $\bar{\beta}$ is the mean beta of the 10,000 simulated beta coefficients, and B is the number of simulations. In other words, se($\hat{\beta}$) is simply the standard deviation of the estimated values of beta across the 10,000 simulations. The new bias-adjusted t-statistic can be calculated as follows:

$$\hat{t}_{adj} = \frac{\ddot{\beta}_{adj}}{se(\hat{\beta})}, \tag{A-5}$$

where the numerator is the bias-adjusted beta coefficient and the denominator is the bootstrap standard error. Because t-statistics constructed in this fashion do not always follow the t-distribution in finite samples, standard critical values may not be appropriate for inference. Therefore, I utilize two alternative approaches to compute p-values based on a bootstrap distribution of t-statistics to yield a more accurate test of the null hypothesis.

The first step in both approaches is to calculate an adjusted t-statistic for each of the 10,000 simulations, thus creating a new empirical distribution of t-statistics. This test statistic is calculated as follows:

$$\hat{t}_i^* = \frac{\ddot{\beta}_i - \bar{\beta}}{se(\hat{\beta})}, \tag{A-6}$$

where $\hat{\beta}_i$ is the estimated beta coefficient for iteration i of the simulation procedure, $\bar{\beta}$ is the mean beta coefficient across the 10,000 simulations, and se($\hat{\beta}$) is the bootstrap standard error. An appealing aspect of this technique is that I am able to construct an empirical distribution of test statistics that adheres closely to the normal distribution, yet provides new critical values for inference.

The first approach for calculating a bootstrap p-value can be depicted as follows:

$$\hat{p}_s = \frac{1}{B} \sum_{i=1}^{B} (|\hat{t}_i^*| > |\hat{t}_{adj}|), \tag{A-7}$$

where $|\hat{t}_i^*|$ is the absolute value of the simulated t-statistic of iteration i that is specified in Equation A-6, $|\hat{t}_{adj}|$ is the absolute value of the bias-adjusted t-statistic detailed in Equation A-5, and B is the number of simulations. This approach implicitly assumes the distribution of the test statistic is symmetric around zero.

Because the empirical distribution of test statistics may not always be entirely symmetric around zero, I compute an alternative p-value as follows:

$$\hat{p}_{ns} = 2 \min \left(\frac{1}{B} \sum_{i=1}^{B} (\hat{t}_i^* > \hat{t}_{adj}), \frac{1}{B} \sum_{i=1}^{B} (\hat{t}_i^* < \hat{t}_{adj}) \right), \tag{A-8}$$

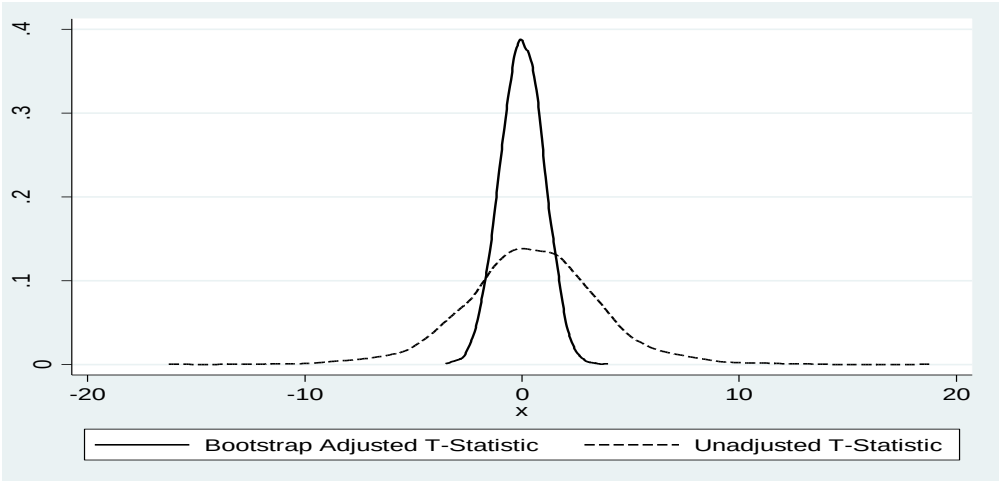
where $\hat{t}_i^*$ is the simulated t-statistic calculated in Equation A-6, $\hat{t}_{adj}$ is the bias-adjusted t-statistic calculated in Equation A-5, and B is the number of simulations. Unlike the previous specification, this technique does not assume the empirical distribution of test statistics is symmetric around zero. MacKinnon (2006) points out that these two approaches could very well lead to significantly different results if the mean value of the simulated t-statistics is vastly different from zero. However, I find that these two approaches yield essentially identical p-values, thus implying that the empirical distributions of test statistics in the present study are virtually symmetric around zero. Reported p-values are calculated based on the first specification detailed in Equation A-7.

Impact of Bootstrap Simulation Adjustments

Figure A-1 provides a graphical illustration of the bootstrap simulation adjustment. Panel A displays the empirical distributions of unadjusted and adjusted t-statistics. The solid line represents the bootstrap-adjusted t-statistics, as depicted in Equation A-6, while the dashed line represents the unadjusted t-statistic, which is calculated using the OLS beta coefficient and

Newey-West standard error. In this case, the unadjusted test statistic distribution has thick tails. Thus, standard inference would result in a rejection of the null hypothesis that sentiment does not affect long horizon returns more often than is actually the case. For example, the empirical distribution of the unadjusted t-statistics falls below the critical value of -1.96 19.62% of the time. The adjusted t-statistics, on the other hand, more closely resemble a normal distribution. In fact, 2.45% of the empirical distribution of simulation-adjusted t-statistics falls below the critical value of -1.96 in the particular example shown.

Panel B displays the empirical distribution of unadjusted and adjusted coefficient estimates from the bootstrap simulation. The solid line represents bootstrap-adjusted coefficients, while the dashed line represents OLS coefficient estimates. The distribution of unbiased coefficient estimates, under the null hypothesis that investor sentiment does not affect long horizon returns, should be centered on zero. However, the unadjusted coefficients appear to be biased, as the empirical distribution is centered slightly to the right of zero, with a median value of 0.0005. Therefore, bias-adjusted coefficient estimates are reported and are used to calculate the adjusted test statistics.



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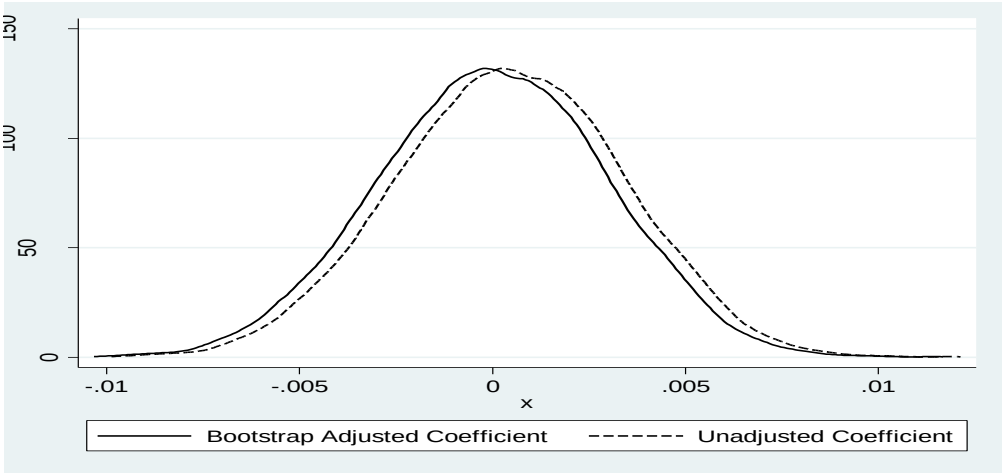

B

Figure A-1. Empirical distribution of bootstrap test statistics and coefficient estimates. A) This figure provides a graphical illustration of the impact of the bootstrap simulation adjustment on the test statistics used for inference. In particular, this figure displays the distributions of unadjusted and adjusted t-statistics. The solid line represents bootstrap-adjusted t-statistics, while the dashed line represents unadjusted t-statistics, which are calculated using the unadjusted OLS coefficient estimate and Newey-West standard error. B) This figure provides a graphical illustration of the impact of the bootstrap simulation adjustment on the coefficient estimates from the long-horizon regressions. In particular, this figure displays the empirical distribution of unadjusted and adjusted coefficient estimates for the measure of investor sentiment. The solid line represents the bootstrap-adjusted coefficients, while the dashed line represents the unadjusted OLS coefficient estimates. This example utilizes returns in public commercial real estate markets, REITRET, at the four year horizon as the dependent variable and the direct measure of investor sentiment, DRES, as the independent variable.

LIST OF REFERENCES

Adrian, T., and H. Shin. 2010. Liquidity and Leverage. *Journal of Financial Intermediation* 19(3): 418-437.

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5(1): 31-56.

Andrews, D. W. 1991. Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica* 59(3): 817-858.

Anilowski, C., M. Feng, and D. Skinner. 2007. Does Earnings Guidance Affect Market Returns? The Nature and Information Content of Aggregate Earnings Guidance. *Journal of Accounting and Economics* 44: 36-63.

Baker, M., and J. Stein. 2004. Market Liquidity as a Sentiment Indicator. *Journal of Financial Markets* 7: 271-299.

Baker, M., and J. Wurgler. 2000. The Equity Share in New Issues and Aggregate Stock Returns. *Journal of Finance* 55(5): 2219-2257.

Baker, M., and J. Wurgler. 2004. A Catering Theory of Dividends. *Journal of Finance* 59(3): 1125-1165.

Baker, M., and J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61(4): 1645-1680.

Baker, M., and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *The Journal of Economic Perspectives* 21 (2): 129-151.

Baker, M., J. Wurgler, and Y. Yuan. 2009. Global, Local, and Contagious Investor Sentiment. Working Paper, Harvard University.

Barinov, A. 2010. Turnover: Liquidity or Uncertainty? Working Paper, University of Georgia.

Barber, B., and T. Odean. 2008. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *The Review of Financial Studies* 21(2): 785-818.

Barberis, N., A. Shleifer and J. Wurgler. 2005. Comovement. *Journal of Financial Economics* 75: 283-317.

Bergman, N. K., and S. Roychowdhury. 2008. Investor Sentiment and Corporate Disclosure. *Journal of Accounting Research* 46(5): 1057-1083.

Bernanke, B., and M. Gertler. 1989. Agency Costs, Net Worth, and Business Fluctuations. *American Economic Review* 79: 14-31.

Bernstein, P. 2007. *Capital Ideas Evolving*. John Wiley & Sons, Inc.: Hoboken, New Jersey.

Boyson, N., C. Stahel, and R. Stulz. 2010. Hedge Fund Contagion and Liquidity Shocks, forthcoming *Journal of Finance.*

Brown, G. W., and M. T. Cliff. 2004. Investor Sentiment and the Near Term Stock Market. *Journal of Empirical Finance* 11: 1-27.

Brown, G. W., and M. T. Cliff. 2005. Investor Sentiment and Asset Valuation. *Journal of Business* 78(2): 405-440.

Brown, N. C., T. E. Christensen, W. B. Elliot and R. Mergenthaler Jr. 2011. Investor Sentiment and Pro Forma Earnings Disclosures. Working Paper, Georgia State University.

Brown, S. J., W. N. Goetzmann, T. Hiraki, N. Shiraishi, and M. Watanabe. 2002. Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows. NBER Working Paper.

Brunnermeier, M. 2009. Deciphering the Liquidity and Credit Crunch 2007-2008. *Journal of Economic Perspectives* 23(1): 77-100.

Brunnermeier, M., and L. Pedersen. 2009. Market Liquidity and Funding Liquidity. *The Review of Financial Studies 22(6):* 2201-2238.

Carhart, M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52(1): 57-82.

Chan, J., D. Hong, and M. Subrahmanyam. 2008. A Tale of Two Prices: Liquidity and Asset Prices in Multiple Markets. *Journal of Banking and Finance* 32: 947-960.

Chan, S., J. Erickson and K. Wang. 2003. Real Estate Investment Trusts: Structure, Performance, and Investment Opportunities. Oxford University Press: New York.

Chen, N., R. Roll, and S. Ross. 1986. Economic Forces and the Stock Market. *Journal of Business* 59: 383-403.

Christensen, T. E., K. J. Merkley, J. W. Tucker and S. Venkataraman. 2011. Do Managers Use Earnings Guidance to Influence Street Earnings Exclusions? *Review of Accounting Studies*, forthcoming.

Chuk, E., D. Matsumoto and G. Miller. 2009. Assessing Methods of Identifying Management Forecasts: CIG vs. Research Collected. Working Paper, University of Washington.

Clayton, J., D. C. Ling, and A. Naranjo. 2009. Commercial Real Estate Valuation: Fundamentals Versus Investor Sentiment. *Journal of Real Estate Finance and Economics* 38: 5-37.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance* 53: 1839-1886.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Noise Trader Risk in Financial Markets. *Journal of Political Economy* 98: 703-738.

Dudley, E., and M. Nimalendran. 2010. Margins and Hedge Fund Contagion. *Journal of Financial and Quantitative Analysis*, forthcoming.

Dye, R. 1985. Disclosure of Nonproprietary Information. *Journal of Accounting Research* 23(1): 123-145.

Dye, R. 1998. Investor Sophistication and Voluntary Disclosures. *Review of Accounting Studies* 3: 261-287.

Economist. 2010. Bubble Warning. 7 January 2010.

Efron, B. 1979. Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics* 7(1): 1-26.

Fama, E. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance* 25: 383-417.

Fama, E., and K. French. 1988. Dividend Yields and Expected Stock Returns. *Journal of Financial Economics* 22(1): 3-25.

Fama, E., and K. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33: 3-56.

Fama, E., and K. French. 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51(1): 55-83.

Fama, E., and G. W. Schwert. 1977. Asset Returns and Inflation. *Journal of Financial Economics* 5:115–46.

Ferson, W.F., and C.R. Harvey. 1991. The Variation of Economic Risk Premiums. *Journal of Political Economy* 99: 385-415.

Fisher, J., D. Gatzlaff, D. Geltner, and D. Haurin. 2004. An Analysis of the Determinants of Transaction Frequency of Institutional Commercial Real Estate Investment Property. *Real Estate Economics* 32(2): 239-264.

Fisher, J., D. Geltner, and H. Pollakowski. 2007. A Quarterly Transactions-Based Index (TBI) of Institutional Real Estate Investment Performance and Movements in Supply and Demand. *Journal of Real Estate Finance and Economics* 34: 5-33.

Fisher, J., and M. Young. 2000 Institutional Property Tenure: Evidence from the NCREIF Database. *Journal of Real Estate Portfolio Management* 6 (4): 327-338.

Fishman, M., and K. Hagerty. 2003. Mandatory versus Voluntary Disclosure in Markets with Informed and Uninformed Customers. *The Journal of Law, Economics, and Organization* 19(1): 45-63.

Frazzini, A., and O. A. Lamont. 2008. Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns. *Journal of Financial Economics* 88: 299-322.

Froot, K., D. Scharfstein, and J. Stein. 1992. Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation. *Journal of Finance* 47(4): 1461-1484.

Froot, K., and E.M. Dabora. 1999. How are Stock Prices Affected by the Location of Trade? *Journal of Financial Economics* 53(2): 189-216.

Garleanu, N., and L. Pedersen. 2007, Liquidity and risk management. *American Economic Review* 97: 193–197.

Geanakoplos, J. 2003. Liquidity, Default, and Crashes: Endogenous Contracts in General Equilibrium. *Advances in Economics And Econometrics: Theory and Applications, Eighth World Conference, Econometric Society Monographs (2)*: 170-205.

Geltner, D., and D. C. Ling. 2007. Indices for Investment Benchmarking and Return Performance Analysis in Private Real Estate. *International Real Estate Review* 10(1): 93-138.

Ghysels, E., A. Plazzi, and R. Valkanov. 2007. Valuation in US Commercial Real Estate. *European Financial Management* 13(3): 472-497.

Glushkov, D. 2006. Sentiment Beta. Working Paper, University of Texas-Austin.

Goetzmann, W. N., and P. Jorion. 1993. Testing the Predictive Power of Dividend Yields. *Journal of Finance* 48(2): 663-679.

Goto, S., M. Watanabe and Y. Xu. 2009. Strategic Disclosure and Stock Returns: Theory and Evidence from US Cross-Listing. *The Review of Financial Studies* 22(4): 1585-1620.

Green, T., and B. Hwang. 2009. Price-Based Return Comovement. *Journal of Financial Economics* 93: 37-50.

Greenwood, R. 2008. Excess Comovement: Evidence from Cross-Sectional Variation in Nikkei 225 Weights. *The Review of Financial Studies* 21: 1153-1186.

Grossman, S. J. 1981. The Informational Role of Warranties and Private Disclosure about Product Quality. *Journal of Law and Economics* 24: 461-489.

Grossman, S. J., and O. Hart. 1980. Disclosure Laws and Takeover Bids. *Journal of Finance* 35(2): 323-334.

Haggard, K., X. Martin and R. Pereira. 2008. Does Voluntary Disclosure Improve Stock Price Informativeness? *Financial Management* 37: 747-768.

Hameed, A., W. Kang, and S. Viswanathan. 2010. Stock Market Declines and Liquidity. *Journal of Finance* 65(1): 257-293.

Hansen, C., and B. Tuypens. 2004. Long-Run Regressions: Theory and Application to US Asset Markets. Working Paper, CUNY.

Hansen, L., and R. Hodrick. 1980. Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Empirical Analysis. *Journal of Political Economy* 88: 829-853.

Houston, J., B. Lev, and J. W. Tucker. 2010. To Guide or Not to Guide? Causes and Consequences of Stopping Quarterly Earnings Guidance. *Contemporary Accounting Research* 27(1): 143-185.

Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance* 48(1): 65–91.

Jiang, G., D. Xu and T. Yao. 2009. The Information Content of Idiosyncratic Volatility. *Journal of Financial and Quantitative Analysis* 44(1): 1-28.

Jin, L., and S. Myers. 2006. R^2 Around the World: New Theory and New Tests. *Journal of Financial Economics* 79(2): 257-292.

Kaplan, S., and A. Schoar. 2005. Private Equity Performance: Returns, Persistence and Capital Flows. *Journal of Finance* 60: 1791-1823.

Kasznik, R., and B. Lev. 1995. To Warn or Not to Warn: Management Disclosures in the Face of an Earnings Surprise. *The Accounting Review* 70(1): 113-134.

Kiyotaki, N., and J. Moore. 1997. Credit Cycles. *Journal of Political Economy* 105(2): 211-248.

Kumar, A., and C. Lee. 2006. Retail Investor Sentiment and Return Comovements. *Journal of Finance* 61(5): 2451-2486.

Lamont, O., and R. Thaler. 2003a. Can the Market Add and Subtract? Mispricing in Tech Stock Carve-outs. *Journal of Political Economy* 111(2): 227-268.

Lamont, O., and R. Thaler. 2003b. Anomalies: The Law of One Price in Financial Markets. *Journal of Economic Perspectives* 17(4): 191-202.

Lee, C., A. Shleifer, and R. Thaler. 1991. Investor Sentiment and the Closed-End Fund Puzzle. *Journal of Finance* 46: 75-109.

Lettau, M., and S. Ludvigson. 2001. Resurrecting the (C) CAPM: A Cross-Sectional Test When Risk Premia are Time-Varying. *Journal of Political Economy* 109(6): 1238-1287

Liew, J. and M. Vassalou. 2000. Can Book-to-Market, Size and Momentum be Risk Factors that Predict Economic Growth? *Journal of Financial Economics* 57: 221-245.

Longstaff, F. and J. Wang. 2008. Asset Pricing and the Credit Market. Working Paper, MIT.

Lown, C., D. Morgan, and S. Rohatgi. 2000. Listening to Loan Officers: The Impact of Commercial Credit Standards on Lending and Output. *Federal Reserve Bank of New York Policy Review* (July): 1-16.

MacKinnon, J. 2002. Bootstrap Inference in Econometrics. *Canadian Journal of Economics* 35(4): 615-645.

MacKinnon, J. 2006. Bootstrap Methods in Econometrics. *The Economic Record* 82: S2-S18.

MacKinnon, J., and A. Smith. 1998. Approximate Bias Correction in Econometrics. *Journal of Econometrics* 85: 205-230.

Menkhoff, L., and R. Rebitzky. 2008. Investor Sentiment in the US-dollar: Longer-Term, Non-Linear Orientation on PPP. *Journal of Empirical Finance* 15: 455-467.

Nelson, C., and M. Kim. 1993. Predictable Stock Returns: The Role of Small Sample Bias. *Journal of Finance* 48(2): 641-661.

Newey, W., and K. West. 1987. A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55: 703-708.

Pagliari, J., K. Scherer, and R. Monopoli. 2005. Public Versus Private Real Estate Equities: A More Refined, Long-Term Comparison. *Real Estate Economics* 33(1): 147-187.

Pastor, L., and R. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111(3): 642-685.

Pontiff, J. 1996. Costly Arbitrage: Evidence from Closed-End Funds. *Quarterly Journal of Economics* 111: 1135-1151.

Pontiff, J. 2006. Costly Arbitrage and the Myth of Idiosyncratic Risk. *Journal of Accounting and Economics* 42: 35-52.

Qiu, L., and I. Welch. 2005. Investor Sentiment Measures. NBER Working Paper.

Rees, L., and R. Wynalda. 2008. An Examination of First Call's Company Issued Guidance Database. *Advances in Accounting* 23: 147-177.

Riddiough, T., M. Moriarty, and P. Yeatman. 2005. Privately Versus Publicly Held Asset Investment Performance. *Real Estate Economics* 33(1): 121-146.

Ritter, J. 1991. The Long-run Performance of Initial Public Offerings. *Journal of Finance* 46: 3-27.

Scheinkman, J., and W. Xiong. 2003. Overconfidence and Speculative Bubbles. *Journal of Political Economy* 111(6): 1183-1219.

Schmeling, M. 2007. Institutional and Individual Sentiment: Smart Money and Noise Trader Risk? *International Journal of Forecasting* 23: 127-145.

Schmeling, M., and A. Schrimpf. 2008. Expected Inflation, Expected Stock Returns, and Money Illusion: What Can We Learn from Survey Expectations? Working Paper, .Humboldt University.

Seybert, N., and H. Yang. 2011. The Party's Over: The Role of Earnings Guidance in Resolving Sentiment-Driven Overvaluation. *Management Science* (Special Issue on Behavioral Economics and Finance), forthcoming.

Sharpe, S. 2002. Reexamining Stock Valuation and Inflation: The Implications of Analysts' Earnings Forecasts. *Review of Economics and Statistics* 84:632–48.

Shleifer, A., and R. Vishny. 1997. The Limits of Arbitrage. *Journal of Finance* 52: 35-55.

Shleifer, A., and R. Vishny. 2010. Unstable Banking. *Journal of Financial Economics* 97*:* 306-318.

Soffer, L., S. R. Thiagarajan and B. Walther. 2000. Earnings Preannouncement Strategies. *Review of Accounting Studies* 5(1): 5-26.

Stambaugh, R. 1999. Predictive Regressions. *Journal of Financial Economics* 54: 375-421.

Veldkamp, L. 2006. Information Markets and the Comovement of Asset Prices. *The Review of Economic Studies* 73(3): 823-845.

Verrecchia, R. 1983. Discretionary Disclosure. *Journal of Accounting and Economics* 5: 179-194.

Welch, I. 1992. Sequential Sales, Learning, and Cascades. *Journal of Finance* 47(2): 695-732.

Wurgler, J., and E. Zhuravskaya. 2002. Does Arbitrage Flatten Demand Curves for Stocks? *Journal of Business* 75(4): 583-608.

BIOGRAPHICAL SKETCH

Benjamin received a Bachelor of Science degree in economics, a Bachelor of Science degree in business administration (finance), and a minor certificate in mathematics from Villanova University in 2003. He was awarded the Bartley Medallion in Economics by the College of Commerce and Finance, the highest distinction the college can award to a graduating student. In 2003, Benjamin joined Navigant Consulting as an Associate Consultant. Over a three year period, Benjamin was involved in several projects that included working within the private wealth management division of a major investment bank, designing and implementing a reporting system for the account reconciliation team of a hedge fund administrator, and performing an audit of the real estate investment division of a prominent insurance company. Benjamin left Navigant Consulting as a Senior Consultant to pursue his Ph.D. in finance at the University of Florida. Benjamin received his Ph.D. from the University of Florida in 2011 and joined the faculty at the University of Georgia as an Assistant Professor of Real Estate.