Three Essays on Market Efficiency and Limits to Arbitrage

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ABSTRACT
(Academic)

This dissertation consists of three essays. The first essay focuses on idiosyncratic volatility as a primary arbitrage cost for short sellers. Previous studies document (i) negative abnormal returns for high relative short interest (RSI) stocks, and (ii) positive abnormal returns for low RSI stocks. We examine whether these market inefficiencies can be explained by arbitrage limitations, especially firms' idiosyncratic risk. Consistent with limits to arbitrage hypothesis, we document an abnormal return of -1.74% per month for high RSI stocks (>=95th percentile) with high idiosyncratic volatility. However, for similar level of high RSI, abnormal returns are economically and statistically insignificant for stocks with low idiosyncratic volatility. For stocks with low RSI, the returns are positively related to idiosyncratic volatility. These results imply that idiosyncratic risk is a potential reason for the inability of arbitrageurs to extract returns from high and low RSI portfolios.

The second essay investigates market efficiency in the absence of limits to arbitrage on short selling. Theoretical predictions and empirical results are ambiguous about the effect of short sale constraints on security prices. Since these constraints cannot be eliminated in equity markets, we use trades from futures markets where there is no distinction between short and long positions. With no external constraints on short positions, we document a weekend effect in futures markets which is a result of asymmetric risk between long and short positions around weekends. The premium is higher in periods of high volatility when short sellers are unwilling to accept higher levels of risk. On the other hand, riskiness of long positions does not seem to have a similar impact on prices.

The third essay studies investor behaviors that generate mispricing by examining relationship between stock price and future returns. Based on traditional finance theory, valuation should not depend on nominal stock prices. However, recent literature documents that preference of retail investors for low price stocks results in their overvaluation. Motivated by this preference, we re-examine the relationship between stock price and expected return for the entire U.S. stock market. We find that stock price and expected returns are positively related if price is not confounded with size. Results in this paper show that, controlled for size, high price stocks significantly outperform low price stocks by an abnormal 0.40% per month. This return premium is attributed to individual investors' preference for low price stocks. Consistent with costly arbitrage, the return differential between high and low price stocks is highest for the stocks which are difficulty to arbitrage. The results are robust to price cut-off of $5, and in different sub-periods.

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ABSTRACT
(Public)

Efficient pricing of an asset is one of the most important functions of any market. It enables market participants to get a fair value in exchange of their asset. However, over the last several decades, complexity of the U.S. financial markets has increased exponentially. Therefore, it is extremely important to analyze various economic and behavioral aspects that impact the pricing of assets (stocks, bonds, etc.). Market price of an asset is supposed to correctly reflect all the available information that affects that particular asset. If the information is positive, then the asset price should go up and vice versa. Thus, any restriction on the incorporation of information in prices could lead to incorrect pricing.

The objective of this dissertation is to contribute to our understanding of various restrictions (or frictions) on information incorporation which leads to incorrect pricing of assets in financial markets. A significant characteristic which restricts market participants to buy or sell is risk associated with that asset. If investors perceive any asset to be risky, then they may either avoid taking positions in that asset or demand a higher return to justify taking additional risk. Therefore, asset-specific risk makes it difficult to incorporate negative or positive information in prices, which leads to incorrect pricing of assets.

In addition, we document the significance of stock prices in predicting future returns. Specifically, we find that, on average, for similar level of market capitalization (total worth of a company), a stock with higher price performs better than a stock with lower price. The reason for this phenomenon is related to the preferences of individual investors for low price stocks. Individual investors think of stocks with low price as lottery stocks. This result has implications for welfare of individual investors. It teaches them not to invest in a stock because it is cheap but to rely on fundamental information in making their investment decisions.

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Introduction

Market efficiency and investors' rationality have long been the anchors of financial economics. Early researchers believed that prices reflect fundamentals because any mispricing created by uninformed or less informed investors would be quickly eliminated by arbitrageurs. However, over the last decades, many cross-sectional asset price anomalies have been discovered and documented by financial researchers. A majority of these empirical anomalies are a result of incomplete arbitrage. Consequently, literature presents alternative asset pricing theories in which arbitrage is not completed by sophisticated arbitrageurs because of various limits to arbitrage which delays the flow of wealth from unsophisticated or irrational investors to rational investors (Shleifer and Vishny, 1997). Furthermore, research in this area is evolving and covering a broader spectrum, highlighting the impact of preferences of financial institutions and limits to arbitrage on asset prices.

It is therefore intriguing to examine the importance and implications of arbitrage costs on market efficiency. In this dissertation, the primary focus is to study the impact of limits to arbitrage and investors' preferences on asset prices. Literature documents different limits to arbitrage, namely idiosyncratic volatility, illiquidity, etc. Shleifer and Vishny (1997) and Pontiff (2006) identify idiosyncratic volatility as a primary arbitrage holding cost. Therefore, a risk-averse investor will avoid taking a large position (long or short) in a stock with high idiosyncratic risk because it will increase the risk of her/his overall portfolio.

In the first essay, the objective is to provide a rational explanation for the negative (positive) relationship between stocks with high (low) relative short interest and subsequent abnormal returns by focusing on idiosyncratic risk as an arbitrage cost for short sellers (buyers). The results are consistent with the notion that idiosyncratic risk restricts short sellers (buyers) from taking enough positions to remove overvaluation (undervaluation) from stock prices, which causes mispricing to persist in the future.

The above findings show that arbitrage costs are potentially the primary reasons behind this mispricing. This leads us to ask the following question: Does the mispricing go away if we remove these limits to arbitrage? This question forms the basis of the second essay, where we examine the impact of frictionless short selling on asset prices. Since it is difficult to remove all the constraints (limits to arbitrage) from equity market, we test our hypothesis in futures markets where there is no distinction between short and long positions. We find that frictionless short selling results in unbiased prices in futures markets. Additionally, a weekend effect in futures markets is documented which is a result of asymmetric risk between long and short positions around weekends.

The third essay studies investors' preferences that generate mispricing and the impact of limits to arbitrage on this mispricing. Specifically, we examine the relationship between stock price and future returns, after explicitly controlling for size. We document a positive relationship between residual stock price and future returns and attribute this relationship to the preferences of firms' investor clientele. Moreover, the return differential between high and low price stocks is highest for the stocks which are difficulty to arbitrage.

Essay 1 is sole-authored by Jitendra Tayal. Essays 2 and 3 are co-authored by Jitendra Tayal and Vijay Singal.

Essay 1

Does Idiosyncratic Volatility Limit Arbitrage? Evidence from Short Selling

1. Introduction

Divergence of opinions coupled with short sale constraints create an upward bias in security prices (Miller, 1977), leading to subsequent negative returns. The cross-sectional predictions of this hypothesis have resulted in many empirical studies. A set of these empirical studies focus on the relationship between level of short selling and future returns, and document a highly significant negative relationship (Asquith and Meulbroek, 1995; Dechow et al., 2001; Desai et al., 2002; and Asquith et al., 2005). One of the studies that focus on the low short interest portfolios is Boehmer, Huszar and Jordan (2010) in which the authors present an empirical analysis and show that stocks with low short interest experience statistically significant positive abnormal returns. However, it remains unclear why rational investors do not quickly arbitrage this known and predictable mispricing.

Researchers examine and explain the existence of this negative relationship between short interest and returns from the perspective of lending constraints (D'Avolio, 2002; Boehme et al., 2006) and supply constraints on short selling (Asquith et al., 2005). D'Avolio (2002) argues that it is very likely that the lending fees on shorted shares or supply constraints can explain the lack of arbitrage. Consistent with their argument, lending fees, as estimated by D'Avolio (2002) and Boehme et al. (2006), for a firm with high level of short interest varies between 0.15% and 0.17% per month, which can explain a portion of the abnormal return, which can exceed 1%, for highly shorted stocks. Institutional ownership, on the other hand, used as a proxy for supply constraint in Asquith et. al. (2005), can also partially explain the abnormal returns for high short interest stocks.

Though there are studies that have done an empirical analysis on the short interest and abnormal return relationship, but there is no study, in my knowledge, that has analyzed this relationship for low and high short interest stocks and the reason behind its persistence. Therefore, in this paper, we examine the relationship between short interest and subsequent returns and provide a rational explanation for the observed mispricing by focusing on the costly arbitrage argument. Specifically, we hypothesize that the reason for the inability of arbitrageurs to extract the abnormal returns can be due to the arbitrage limitations.

There is an extensive literature that talks about different limits to arbitrage, namely idiosyncratic volatility, illiquidity, etc. Idiosyncratic volatility is identified as a primary arbitrage holding cost (Shleifer and Vishny, 1997; Pontiff, 2006). Thus, a risk-averse investor will avoid taking a large position (long or short) in a stock with high idiosyncratic risk because it will increase the risk of her/his overall portfolio. In the standard asset pricing theory, there are studies that show that the expected stock returns are related to the idiosyncratic volatility of the stock. For instance, Ang, Hodrick, Xing, and Zhang (2006, 2009) document a negative relationship between idiosyncratic volatility and future returns. There is much debate on this counter-intuitive relationship. Malkiel and Xu (2006) follow a portfolio-based approach to minimize errors-in-variables problems and find a positive volatility-return relation. Bali and Cakici (2008) construct equal-weighted idiosyncratic volatility portfolios and find that the negative volatility premium is non-existent in these portfolios. However, Doran, Jiang, and Peterson (2008) find that the idiosyncratic volatility premium is negative even in equal-weighted portfolios if January returns are excluded. To capture time-variation in idiosyncratic volatility, some papers (Spiegel and Wang, 2005; Fu, 2009) use EGARCH type models and report a positive volatility-return relation.

On the other hand, Kapadia (2007) and Boyer, Mitton, and Vorkink (2010) show that with idiosyncratic skewness controls, the negative idiosyncratic volatility premium becomes weaker but it is still significantly negative. Overall, the higher idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006) and higher idiosyncratic skewness (Eraker and Ready, 2015; Kumar, 2009) are associated with lower returns. Though these studies use different measures for idiosyncratic volatility, they provide an economic significance of the idiosyncratic risk.

In the context of this research, we hypothesize that the highest positive and negative abnormal returns in case of the low and high short interest portfolios respectively are displayed by the stocks with the highest idiosyncratic risk. Moreover, idiosyncratic risk associated with these stocks prevents arbitrageurs from correcting this mispricing instantaneously. This hypothesis tries to explain the reason for the inability of arbitrageurs (i) to quickly remove the overpricing from the high short interest portfolios, and (ii) to extract the abnormal returns from the low short interest portfolios.

To examine above hypotheses, we divide the high and low short interest data sample into quintiles separately. In this framework, we expect to observe a negative relationship between idiosyncratic volatility and subsequent returns for high short interest stocks. This expectation follows Miller (1977), who argues that higher short selling constraints create overpricing in security prices, leading to subsequent negative returns. However, for low short interest stocks, the relationship between idiosyncratic volatility and future returns is expected to be positive because idiosyncratic volatility acts as an arbitrage limitation for buyers as there is very low demand for short selling (by construction).

Consistent with the literature, the results confirm the negative relationship between high short interest stocks and subsequent abnormal returns. In addition, a significant -1.74% monthly abnormal return for high short interest stocks (>= 95th percentile) with high idiosyncratic volatility is documented. Moreover, the abnormal return is insignificant 0.14% for low idiosyncratic volatility stocks with same level of short interest. These results confirm the one of the main hypothesis of this paper that abnormal negative performance of high short interest stocks is a result of arbitrage limitations. Furthermore, analysis for low short interest stocks displays a positive association between idiosyncratic volatility and subsequent returns. The results are robust to various controls and are not driven by stocks in extreme portfolios.

Among its contributions, this paper is first to analyze high and low short interest portfolios with an emphasis on providing a rational explanation for the observed negative relationship between short interest and future returns. The reminder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data sources and presents the empirical results. Section 4 outlines the implications of the results and concludes.

2. Related Literature

Seneca (1967) is one the earliest studies which examines the impact of aggregate market-wide short interest on subsequent S&P 500 returns and documents a negative relationship. A similar study (Figlewski, 1981) with stock-specific short interest finds a negative correlation between short interest and future excess returns. This bearish signal in level of short interest in confirmed in subsequent studies in various contexts: by examining the supply constraints on short selling (Asquith, Pathak & Ritter, 2005); in the options markets (Pan & Poteshman, 2006); in the Nasdaq markets (Desai et al., 2002); in equity markets as an explanation for the weekend effect (Chen and Singal, 2003). Furthermore, a recent paper (Boehmer, Huszar & Jordan, 2010) provides a complete view of the relationship by examining the low short interest stocks and documents a positive abnormal return for stock with low short interest. Additionally, with the availability of short interest data at higher frequencies, various researchers re-examine the negative relationship between short selling and returns using daily short selling data. For instance, Boehmer, Jones & Zhang (2008) document a significant underperformance of highly shorted stocks for nonprogram institutional trades. Similarly, Aitken et al. (1998) show that in Australia, the direct disclosure of some short sale to the public causes prices to decline immediately.

As documented above, different research papers present a negative association between short interest and returns. This negative relationship seems to be a result of divergence of opinion among investors coupled with constraints on short selling, which may result in an upward bias in prices in the short run. Several papers find support for this hypothesis and show that dispersion in beliefs leads to low subsequent returns (Diether, Malloy & Scherbina, 2002; Chen, Hong & Stein, 2002). Similarly, Boehme et al. (2006) document negative future returns following abnormally high short interest, especially when short selling is constrained and opinions are divergent. However, an opposite effect is observed when a diversity measure of analyst disagreement is used in the analysis (Doukas, Kim and Pantzalis, 2006).

Senchack & Starks (1993) present a different perspective by examining the short-run announcement impact of the public release of short interest reports. They report negative abnormal returns when the short interest is higher than expected. However, later studies (Huszar & Qian, 2012) find that the reported returns are overestimated because lending fees are excluded from the analysis. In addition, the lending fees might constrain short selling activity (D'Avolio, 2002; Geczy, Musto, and Reed, 2002), however recent research (Kaplan, Moskowitz, and Sensoy, 2013) report that an experiment where rebate rates were artificially changed did not result in any noticeable effect on asset prices. To further isolate the effect of supply constraints on prices, researchers have investigated supply shocks (loan fees in Cohen, Diether, Malloy, 2007; option introduction in Sorescu, 2000; and lockup expirations in Ofek and Richardson, 2003) but the results are not convincing according to Kaplan, Moskowitz, and Sensoy (2013).

Several other studies empirically examine the impact of various constraints on short selling. For instance, Asquith, Pathak and Ritter (2005) document that supply constraints on short selling lead to low subsequent returns, and Ofek and Richardson (2003) argue that Internet bubble can be partially explained by short-sale constraints. Similar arguments related to concentration of abnormal returns among constrained stocks are presented in Arnold et al. (2005), Nagel (2005), and Duan, Hu and McClean (2010).

In this paper, we abstract from the traditional way of analyzing different constraints on short selling and focus on idiosyncratic volatility as a limit to arbitrage variable which is known to dissuade short sellers (buyers) from taking position in overvalued (undervalued) securities. In the next sections, details of the sample data and empirical analysis are presented.

3. Empirical Framework

3.1 Data Sources, Sample Construction, and Variable Definitions

The initial sample of short interest includes all the stocks for which mid-month outstanding short shares are available in Compustat Short Interest Supplemental file from 1988 to 2013. All the member firms of NYSE, AMEX, and NASDAQ are required to report aggregate number of shares sold short over all accounts as of middle of each month. These reported short sold shares are compiled and reported by the respective exchanges. The Compustat Short Interest Supplemental file contains data for NYSE and AMEX firms beginning in 1973 and for

NASDAQ beginning in 2003. We supplement the NASDAQ short sale data from 1988 to 2002[1] with those from Compustat from 2003 to 2013.

Monthly stock returns, price and share outstanding for all stocks traded on NYSE, NASDAQ, and AMEX are obtained from CRSP for the period 1988 to 2013. Book value is collected from Compustat. Finally, we get Fama-French (1993) factors and the Carhart (1997) momentum factor from CRSP to calculate four-factor abnormal returns for equal-weighted[2] portfolios. In addition to various stock characteristics, quarterly data on Institutional ownership is acquired from Thomson's Reuters (13-f) holdings from 1988 to 2013. A value of zero is assigned if no institutional ownership is reported for a stock.

The monthly short interest data is combined with monthly return data from 1988 to 2013. Institutional ownership and book value are added to the combined data sample of short interest and returns. As institutional ownership and book value are available at a quarterly frequency, quarter-ending numbers are used for the following two months. Interpolation of these variables is not performed to avoid the look-ahead bias. Relative Short Interest (RSI) is defined as the ratio of total number of shorted shares and total number of shares outstanding at the end of each month. Institutional ownership (IO) is calculated by dividing the total number of shares owned by institutions with total number of outstanding shares. Book-to-market (B/M) is the ratio of book value of a stock to its market capitalization, which is equal to the product of price and shares outstanding at the end of each month. Idiosyncratic volatility and idiosyncratic skewness are calculated as second and third moments of the residuals by implementing Fama-French-Carhart (FFC) four-factor model on daily returns. To avoid stocks with infrequent trading and following (Fu, 2009), stocks with at least 15 trading days in a month are selected for the analysis.

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[1] I thank Vijay Singal for providing me with the short sale data for NASDAQ firms from 1988 to 2002.

[2] Equal-weighted portfolio returns are used for the entire analysis.

3.2 Sample Characteristics

In this section, sample characteristics of firms with high and low short interest are documented. I start the analysis by dividing the sample into percentiles based on previous month's relative short interest. Figure 1.1 plots the time series of relative short interest and institutional ownership from 1988 to 2013. Specifically, the median and 95th percentiles of relative short interest, and the median institutional ownership for all stocks and median institutional ownership for stocks in the 95th percentile (based on short interest) are presented. In keeping with results of Asquith, Pathak and Ritter (2005), short interest for a typical firm has remained low for the entire sample period. The 95th percentile, or the top 5% of the sample based on relative short interest displays a median RSI of around 10%, with a substantial increase during 2008 financial crisis. However, median institutional ownership for the whole sample has remained substantially higher than median short interest for the entire sample period. Moreover, median institutional ownership for firms in 95th percentile (based on short interest) is substantially higher than the median relative short interest for the same group. This implies that supply constraint, proxied by institutional ownership (Asquith, Pathak and Ritter, 2005), is not binding for majority of firms falling in high short interest group.

Please insert Figure 1.1 here

Continuing with the analysis, high and low short interest portfolios are constructed based on relative values of RSI. Specifically, relative cut-offs at 90th and 95th percentiles are implemented for high RSI portfolios. Similarly, 10th and 5th percentile are used as cutoffs for constructing low RSI portfolios. Panel A and Panel B of Table 1.1 report various firm characteristics of high and low RSI portfolios respectively. The mean firm size (market capitalization) is higher for high RSI portfolios than that of low RSI portfolios, suggesting that firms with low levels of short interest tend to be much smaller in size. Further, the results suggest that book-to-market (B/M) is higher for low RSI portfolios. However, this variation is small when we move within low and high RSI groups. Interestingly, average institutional ownership for these high short interest portfolios is substantially higher (62% for relative RSI >= 95th percentile) than relative short interest (14.87%) for the same group. These results further strengthen the argument that supply constraints are not binding for short sellers for majority of stocks with high short interest. In addition, low RSI portfolios display lower price, higher idiosyncratic volatility, and higher Amihud's (2002) illiquidity than those of high RSI portfolios. However, idiosyncratic skewness does not display any variation within or across high and low RSI portfolios.

Please insert Table 1.1 here

3.3 <u>Returns for High and Low Short Interest Stocks</u>

In this section, the negative relationship between short interest and future returns is examined for high and low short interest stocks. After classifying firms based on their previous month's relative RSI, raw returns and FFC four-factor model parameters including the abnormal returns (alphas) are reported in Table 1.2. The results displayed suggest that high (low) short interest is followed by statistically significant negative (positive) abnormal returns, which is in confirmation with the literature. The 95th percentile portfolio has a -0.65% abnormal return per month, which is similar in magnitude to those reported in Asquith et al. (2005). Moreover, both raw and four-factor alphas are higher for low RSI portfolios when compared to those of high RSI portfolios.

In addition to documenting a negative (positive) abnormal return for high (low) RSI stocks, portfolio abnormal returns are calculated by excluding firms with extreme RSI to test whether the returns concentrated in extreme stocks. The four-factor alpha of -0.51% for portfolio with RSI between 90th and 95th percentile, and an alpha of 1.05% for portfolio with RSI between 6th and 10th percentile confirm that negative (positive) returns, rather than concentrated in extreme short interest portfolios, are uniformly present in high (low) RSI portfolios. Similar results are obtained when different cut-offs of relative RSI are implemented.

Please insert Table 1.2 here

3.4 <u>Descriptive Statistics for Idiosyncratic Volatility Portfolios</u>

Sample period averages of several important characteristics of high and low RSI portfolios for quintiles based on idiosyncratic volatility are examined. High short interest portfolios are constructed based on different levels of previous month's relative short interest. We choose portfolio with relative RSI >= 95th percentile[3] as high RSI portfolio and portfolio with relative RSI <= 5th percentile as low RSI portfolio. Following our hypothesis, high and low RSI samples are independently divided into quintiles based on idiosyncratic volatility.

The summary statistics for portfolios based on idiosyncratic volatility within high and low short interest portfolios are presented in Panel A and Panel B of Table 1.3 respectively. The results indicate that size decreases from $1675 to $496 million for high short interest portfolios with the increase in idiosyncratic volatility. This is consistent with the argument that small size firms are more volatile. However, book-to-market increases with idiosyncratic volatility. Furthermore, within high RSI group, average relative short interest is slightly higher (approximately 30%) for high idiosyncratic volatility group when compared with that of low idiosyncratic volatility group. On the other hand, for low RSI group, RSI does not vary with idiosyncratic volatility and has a value close to 0% for all idiosyncratic volatility quintiles. This

[3] Similar results are obtained when different relative RSI cutoffs are used for analysis.

implies that idiosyncratic volatility would act as a constraint for buyers because there is no demand for short selling. Following Asquith et al. (2005), we report institutional ownership for all idiosyncratic volatility quintiles. The results show that even for the highest idiosyncratic volatility quintile, institutional ownership (48%) is much higher than RSI (16.83%). This implies that supply constraint is not binding for short sellers for any level of idiosyncratic volatility.

Consistent with the literature, the highest idiosyncratic volatility quintile has lower price (almost one third), higher idiosyncratic volatility (3 times) and higher illiquidity when compared to those of the lowest idiosyncratic volatility quintile for high RSI group. The differences in these firm characteristics, i.e. price, idiosyncratic volatility, and illiquidity, between highest and lowest idiosyncratic volatility quintiles are more pronounced and higher for low RSI group. Next, we examine the returns associated with high and low RSI groups for different idiosyncratic volatility groups.

Please insert Table 1.3 here

3.5 *Idiosyncratic Volatility and High Short Interest Stocks*

In this section, the main hypothesis that short sellers avoid taking sufficient positions in risky stocks with high idiosyncratic volatility, resulting in their overvaluation and leading to subsequent negative abnormal returns, is tested. High RSI portfolios are constructed by following the same procedure as in section 3.3. These high RSI portfolios are divided into quintiles based on previous month's idiosyncratic volatility of constituent firms. Raw and FFC four-factor abnormal returns for subsequent months after portfolio construction are calculated and presented in Table 1.4.

The results support our main hypothesis. We observe a highly significant negative abnormal return of -1.56% (-1.74%) per month for the highest idiosyncratic volatility quintile with RSI greater than 90th percentile (95th percentile). A monotonic relationship between idiosyncratic volatility and returns is also documented. Furthermore, abnormal returns for the lowest idiosyncratic volatility quintile stocks (safer stocks) are economically and statistically insignificant across all RSI portfolios. This result strengthens the hypothesis that informed short sellers take sufficient positions in high RSI stocks with low idiosyncratic volatility to remove overvaluation in a short time period.

Additionally, raw and abnormal returns are calculated by excluding firms with extreme RSI to test whether these results are concentrated in these stocks. A statistically significant -1.11% (-1.32%) difference in abnormal (raw) return is observed between the highest and the lowest idiosyncratic volatility groups for portfolios with RSI between 90th and 95th percentile. Overall, these results confirm the assertion that underperformance of high RSI stocks is a result of costly arbitrage, arising mainly from idiosyncratic volatility.

Please insert Table 1.4 here

3.6 *Idiosyncratic Volatility and Low Short Interest Stocks*

As mentioned in the above sections, majority of the literature on short selling focuses on high RSI stocks. However, a recent paper (Boehmer, Huszar & Jordan, 2010) presents a complete view of short selling and return relationship by examining stocks with low short interest and documents a positive abnormal return for stock with low short interest. They do not find a rational reason behind this relationship and argue that this positive abnormal return should not exist given that investors can take a long position to remove this mispricing. In this section, we examine and present a potential reason behind the existence of positive abnormal returns for low RSI stocks.

We hypothesize that the reason for the inability of investors to extract the abnormal returns can be due to arbitrage limitations. The primary arbitrage cost that we examine is idiosyncratic volatility. To test our hypothesis, low RSI portfolios are constructed by following the same procedure as implemented in Section 3.3. These low RSI portfolios are further divided into quintiles based on previous months' idiosyncratic volatility. Raw and FFC four-factor abnormal returns are calculated and reported in Table 1.5.

Consistent with costly arbitrage hypothesis, a positive and monotonic relationship is observed between idiosyncratic volatility and returns within each low RSI group. Moreover, the abnormal return differential between the highest and the lowest idiosyncratic volatility portfolios is a statistically significant 1.02% per month for group with RSI less than 10th percentile. The returns are consistent across all low RSI groups and are not concentrated in extreme RSI portfolios. These results highlight the significance of idiosyncratic volatility as an arbitrage cost and present a potential reason for the existence and persistence of low RSI mispricing.

Please insert Table 1.5 here

3.7 Regression Analysis

To study the impact of various limits to arbitrage variables, firm level Fama-Macbeth (1973) cross-sectional regressions are performed for high (RSI >=95th percentile) and low (RSI <= 5th percentile) RSI portfolios for the period 1988 to 2013. The following regression framework is implemented in which monthly raw returns are regressed on lagged firm-specific characteristics.

$$R_{i,t} = \beta_{0,t} + \sum_{k} \beta_{k,t} X_{i,t-1,k} + \varepsilon_{i,t} \quad (1)$$

where $R_{i,j}$ refers to the monthly raw return for firm i in month t and $X_{i,t-1,k}$ refers to explanatory variables, including dummy variable for high RSI stocks. $\sum_k \beta_{k,t} X_{i,t-1,k}$ represents various combinations of explanatory variables, which are market beta, natural logarithm of size expressed in $millions, book to market, momentum (past 6 months returns[4]), RSI, high RSI dummy, percentage of institutional ownership, idiosyncratic volatility, idiosyncratic skewness, illiquidity, and interaction terms between high RSI dummy and limits to arbitrage variables.

The results of time series average of firm-level Fama-Macbeth (1973) cross-sectional regressions are reported in Table 1.6. Controlling for four known factors, the coefficient on RSI is negative and statistically significant which is consistent with the negative relationship between RSI and subsequent returns. In Column 2, idiosyncratic volatility and its interaction with high RSI dummy are included. The coefficient for the interaction term is negative (-0.46) and highly significant. However, the coefficient for idiosyncratic volatility is positive and statistically significant. These results imply that idiosyncratic volatility is positively related with returns for low RSI stocks and is negatively related with returns for high RSI stocks. Another interesting observation is the sign reversal for coefficient on High RSI after controlling for idiosyncratic volatility. These findings explain the importance of idiosyncratic risk as an arbitrage cost for high and low RSI stocks. The coefficient for the interaction between institutional ownership and high RSI is positive and statistically significant implying that returns are positive for high RSI stocks with higher institutional ownership. This result is in accordance with Asquith et. al (2005) which present low institutional ownership (supply constraint) as a primary reason for observed negative returns for high RSI stocks. However, the coefficient on High RSI dummy is negative and statistically significant, even after controlling for institutional ownership. This implies that

[4] Results are similar when past 12-months returns are used.

institutional ownership cannot completely explain the negative returns associated with high RSI stocks. In addition to the above limits to arbitrage variables, we control for idiosyncratic skewness and illiquidity as well. The results are insignificant for idiosyncratic skewness which is consistent with Table 1.1, where we do not observe any variation in idiosyncratic skewness for high and low RSI stocks. Although the coefficients are significant for illiquidity and its interaction with high RSI dummy, the economic significance of their effect is much smaller than that of idiosyncratic volatility.

Overall, in this multivariate setting, idiosyncratic volatility emerges as the most important arbitrage cost for low as well as high RSI stocks. In the next regression framework, we examine the relative importance of idiosyncratic volatility over other limits to arbitrage variables for high RSI stocks.

Please insert Table 1.6 here

3.8 Regression Analysis for High Short Interest Stocks

To examine the relative importance of idiosyncratic volatility, we implement firm level Fama-Macbeth (1973) cross-sectional regressions for high RSI portfolios for the period 1988 to 2013. The following regression framework is implemented in which monthly raw returns are regressed on lagged firm-specific characteristics.

$$R_{i,t} = \beta_{0,t} + \sum_{k} \beta_{k,t} X_{i,t-1,k} + \varepsilon_{i,t} \quad (2)$$

where $R_{i,j}$ refers to the monthly raw return for firm i in month t and $X_{i,t-1,k}$ refers to explanatory variables, which are market beta, natural logarithm of size expressed in $millions, book to market, momentum, percentage of institutional ownership, idiosyncratic volatility, idiosyncratic skewness, and illiquidity. $\beta_{k,t}$ represents coefficients for explanatory variables.

It is evident from the results reported in Table 1.7 that high idiosyncratic volatility and low institutional ownership are the two most important arbitrage cost for short sellers. However, given that institutional ownership is not binding for short sellers, idiosyncratic volatility is potentially the primary cost that restricts arbitrageurs from exploiting this mispricing.

Please insert Table 1.7 here

4. Conclusion

The negative relationship between short interest and subsequent returns is documented and explained in various research papers. We provide a rational explanation for this relationship for high and low RSI stocks by focusing on idiosyncratic volatility as arbitrage limiting cost. Because of high idiosyncratic risk, we argue that informed short sellers (buyers) are reluctant to take sufficient positions in high (low) RSI stocks, resulting in their overvaluation (undervaluation) and subsequent negative (positive) returns. On the other hand, stocks with low idiosyncratic volatility present safe investment opportunities for short sellers. The results reported in this paper are consistent with this argument. Specifically, for the same level of short interest, the negative (positive) returns are very high for high (low) RSI stocks with high idiosyncratic risk.

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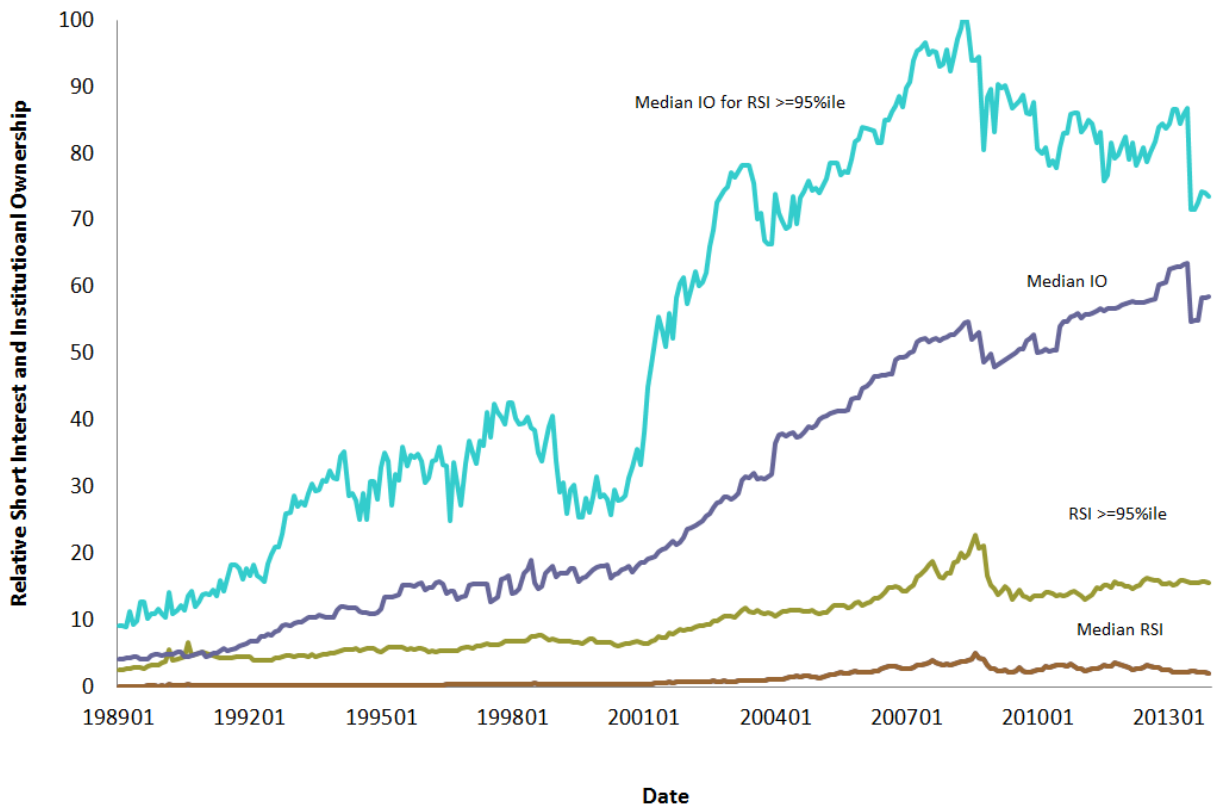

Figure 1.1: Relative Short Interest and Institutional Ownership

The median and 95th percentiles of relative short interest, and the median institutional ownership for all stocks and median institutional ownership for stocks with RSI greater than 95th percentile at the end of the month are presented for 1988 to 2013. Relative short interest is defined as number of shorted shares divided by shares outstanding. If no shorted shares are reported for a stock in a given month, the ratio is assumed to be zero. Institutional ownership is defined as shares held by institutions divided by shares outstanding and is calculated quarterly.

Table 1.1: Descriptive Statistics

Portfolio means of firm characteristics for high and low short interest stocks are reported for the period 1988 to 2013 in Panel A and Panel B respectively. *RSI* refers to relative short interest which is calculated as the ratio of the number of shorted shares and shares outstanding; *Size* refers to market capitalization, expressed in $ millions; *B/M* refers to ratio of book value to market value; *IO* refers to institutional ownership and is calculated as percentage of shares owned by institutions; *IVOL* and *ISKEW* refer to idiosyncratic volatility and idiosyncratic skewness respectively; and *ILLIQ* refers to Amihud's illiquidity measure.

Panel A: High Short Interest Ratio								
RSI Portfolios	Size	B/M	RSI	IO	Price	IVOL	ISKEW	ILLIQ
>=90%ile	1114	0.82	11.04%	60%	22.4	3.03%	0.18	1.53
	145565	*131260*	*145565*	*114989*	*145565*	*145565*	*145537*	*145561*
>=90%ile to <=94%ile	1305	0.78	7.21%	58%	22.8	2.93%	0.18	1.65
	72878	*65592*	*72878*	*57289*	*72878*	*72878*	*72860*	*72876*
>=95%ile	922	0.86	14.87%	62%	22.1	3.12%	0.19	1.40
	72687	*65668*	*72687*	*57700*	*72687*	*72687*	*72677*	*72685*

Panel B: Low Short Interest Ratio								
RSI Portfolios	Size	B/M	RSI	IO	Price	IVOL	ISKEW	ILLIQ
<=10%ile	98	1.13	0.01%	15%	8.7	4.00%	0.18	42.93
	151277	*126842*	*151277*	*105871*	*151277*	*151277*	*147990*	*150316*
>=6%ile to <=10%ile	56	1.07	0.01%	15%	8.5	3.90%	0.17	47.49
	88203	*71153*	*88203*	*59099*	*88203*	*88203*	*84984*	*87408*
<=5%ile	157	1.21	0.00%	16%	9.0	4.13%	0.20	36.59
	63074	*55689*	*63074*	*46772*	*63074*	*63074*	*63006*	*62908*

Table 1.2: Returns for High and Low Short Interest Stocks

Raw and four-factor abnormal returns along with four-factor model parameters for high and low short interest portfolios are reported for the period 1988 to 2013. *MKTRF* the realization of the market risk premium in period, *SMB* is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, *HML* is the return on a portfolio of high book-to-market (value) minus low book-to-market (growth) stocks, and *UMD* is the return on a portfolio of prior winners minus the return on a portfolio of prior losers.

Panel A: High Short Interest Ratio

RSI Portfolios	Raw Returns	FFC 4-F Alpha	MKTRF	SMB	HML	UMD	Adj-R2
>=90%ile	0.52%	-0.58%	1.23	1.05	-0.05	-0.35	94.18%
		(-5.18)	*(45.76)*	*(29.81)*	*(-1.40)*	*(-14.93)*	
>=90%ile to <=94%ile	0.59%	-0.51%	1.23	0.95	-0.03	-0.32	92.95%
		(-4.28)	*(42.85)*	*(25.26)*	*(-0.78)*	*(-12.83)*	
>=95%ile	0.44%	-0.65%	1.24	1.16	-0.07	-0.38	92.33%
		(-4.82)	*(38.07)*	*(27.14)*	*(-1.63)*	*(-13.44)*	

Panel B: Low Short Interest Ratio

RSI Portfolios	Raw Returns	FFC 4-F Alpha	MKTRF	SMB	HML	UMD	Adj-R2
<=10%ile	1.78%	1.05%	0.52	0.65	0.26	-0.23	57.68%
		(5.75)	*(11.81)*	*(11.14)*	*(4.14)*	*(-6.02)*	
>=6%ile to <=10%ile	1.79%	1.05%	0.58	0.69	0.27	-0.20	56.00%
		(5.25)	*(11.88)*	*(10.84)*	*(3.9)*	*(-4.82)*	
<=5%ile	1.76%	1.06%	0.52	0.53	0.20	-0.24	53.81%
		(5.06)	*(10.34)*	*(8.07)*	*(2.84)*	*(-5.64)*	

Table 1.3: Descriptive Statistics for Idiosyncratic Volatility Portfolios

Portfolio means of firm characteristics based on idiosyncratic volatility for high and low short interest stocks are reported for the period 1988 to 2013 in Panel A and Panel B respectively. *RSI* refers to relative short interest which is calculated as the ratio of the number of shorted shares and shares outstanding; *Size* refers to market capitalization, expressed in $ millions; *B/M* refers to ratio of book value to market value; *IO* refers to institutional ownership and is calculated as percentage of shares owned by institutions; *IVOL* and *ISKEW* refer to idiosyncratic volatility and idiosyncratic skewness respectively; and *ILLIQ* refers to Amihud's illiquidity measure.

Panel A: High Short Interest Ratio (95%ile)								
IVOL Portfolios	Size	B/M	RSI	IO	Price	IVOL	ISKEW	ILLIQ
1 (Low)	1675	0.72	12.86%	71%	34.5	1.66%	0.14	0.26
	7106	*6429*	*7106*	*5872*	*7106*	*7106*	*7100*	*7106*
2	1170	0.61	13.96%	69%	27.7	2.29%	0.16	0.11
	14924	*13756*	*14924*	*12364*	*14924*	*14924*	*14924*	*14923*
3	912	0.63	14.54%	64%	22.8	2.82%	0.16	0.10
	19280	*17739*	*19280*	*15465*	*19280*	*19280*	*19280*	*19280*
4	742	0.73	15.35%	58%	18.5	3.46%	0.20	0.32
	18221	*16484*	*18221*	*14088*	*18221*	*18221*	*18219*	*18220*
5 (High)	496	1.81	16.83%	48%	12.8	4.84%	0.26	6.88
	13156	*11260*	*13156*	*9911*	*13156*	*13156*	*13154*	*13156*

Panel B: Low Short Interest Ratio (5%ile)								
IVOL Portfolios	Size	B/M	RSI	IO	Price	IVOL	ISKEW	ILLIQ
1 (Low)	533	0.96	0.00%	21%	16.9	1.53%	0.12	5.88
	9046	*7801*	*9046*	*7348*	*9046*	*9046*	*9013*	*8980*
2	297	1.21	0.00%	18%	14.2	2.22%	0.13	6.04
	8946	*8080*	*8946*	*7123*	*8946*	*8946*	*8941*	*8934*
3	101	1.33	0.00%	17%	11.2	2.89%	0.16	12.00
	10729	*9761*	*10729*	*8382*	*10729*	*10729*	*10724*	*10712*
4	56	1.20	0.00%	15%	7.1	3.88%	0.19	19.57
	13174	*11995*	*13174*	*9937*	*13174*	*13174*	*13163*	*13145*
5 (High)	28	1.26	0.00%	12%	3.4	6.85%	0.28	85.58
	21179	*18052*	*21179*	*13982*	*21179*	*21179*	*21165*	*21137*

Table 1.4: Idiosyncratic Volatility and High Short Interest Stocks

Raw and four-factor abnormal returns for portfolios based on idiosyncratic volatility (*IVOL*) for high short interest portfolios are reported for the period 1988 to 2013. *FFC 4-F Alpha* refers to the abnormal return after controlling for Fama-French three factors and Carhart's momentum factor. *RSI 90%ile* refers to the portfolio of stocks in 90th to 100th percentile based on relative short interest. *RSI 90%ile to RSI 94%ile* refers to the portfolio of stocks in 90th to 94th percentile based on relative short interest. *RSI 95%ile* refers to the portfolio of stocks in 95th to 100th percentile based on relative short interest.

	RSI 90%ile		***RSI 90%ile to RSI 94%ile***		***RSI 95%ile***	
IVOL Portfolios	Raw Returns	FFC 4-F Alpha	Raw Returns	FFC 4-F Alpha	Raw Returns	FFC 4-F Alpha
1 (Low)	1.07%	-0.03%	0.97%	-0.11%	1.26%	0.14%
	(3.85)	*(-0.23)*	*(3.44)*	*(-0.85)*	*(4.19)*	*(0.80)*
2	1.00%	-0.17%	0.93%	-0.25%	1.10%	-0.06%
	(2.80)	*(-1.50)*	*(2.58)*	*(-1.78)*	*(2.94)*	*(-0.41)*
3	0.68%	-0.48%	0.69%	-0.50%	0.66%	-0.48%
	(1.58)	*(-4.10)*	*(1.63)*	*(-3.56)*	*(1.46)*	*(-3.03)*
4	0.52%	-0.55%	0.70%	-0.35%	0.34%	-0.75%
	(0.94)	*(-2.93)*	*(1.3)*	*(-1.61)*	*(0.57)*	*(-3.18)*
5 (High)	-0.62%	-1.56%	-0.36%	-1.22%	-0.74%	-1.74%
	(-0.88)	*(-4.36)*	*(-0.48)*	*(-2.98)*	*(-1.05)*	*(-4.37)*
High - Low	-1.69%	-1.53%	-1.32%	-1.11%	-2.01%	-1.88%
	(-2.89)	*(-3.74)*	*(-2.06)*	*(-2.42)*	*(-3.34)*	*(-4.05)*

Table 1.5: Idiosyncratic Volatility and Low Short Interest Stocks

Raw and four-factor abnormal returns for portfolios based on idiosyncratic volatility (*IVOL*) for low short interest portfolios are reported for the period 1988 to 2013. *FFC 4-F Alpha* refers to the abnormal return after controlling for Fama-French three factors and Carhart's momentum factor. *RSI 10%ile* refers to the portfolio of stocks in 0th to 10th percentile based on relative short interest. *RSI 6%ile to RSI 10%ile* refers to the portfolio of stocks in 6th to 10th percentile based on relative short interest. *RSI 5%ile* refers to the portfolio of stocks in 0th to 5th percentile based on relative short interest.

	RSI 10%ile		***RSI 6%ile to RSI 10%ile***		***RSI 5%ile***	
IVOL Portfolios	Raw Returns	FFC 4-F Alpha	Raw Returns	FFC 4-F Alpha	Raw Returns	FFC 4-F Alpha
1 (Low)	1.27%	0.67%	1.30%	0.67%	1.24%	0.71%
	(7.19)	*(4.54)*	*(6.84)*	*(4.31)*	*(7.09)*	*(4.71)*
2	1.33%	0.66%	1.31%	0.63%	1.35%	0.72%
	(6.47)	*(4.32)*	*(5.80)*	*(3.55)*	*(5.84)*	*(4.04)*
3	1.31%	0.63%	1.35%	0.59%	1.36%	0.79%
	(5.69)	*(3.94)*	*(5.22)*	*(3.14)*	*(5.28)*	*(4.09)*
4	1.69%	0.97%	1.57%	0.85%	1.71%	1.01%
	(5.77)	*(5.14)*	*(5.08)*	*(4.09)*	*(4.88)*	*(4.05)*
5 (High)	2.34%	1.69%	2.46%	1.72%	2.04%	1.45%
	(5.30)	*(5.10)*	*(5.02)*	*(4.51)*	*(4.09)*	*(3.78)*
High - Low	1.07%	1.02%	1.18%	1.07%	0.80%	0.74%
	(2.84)	*(3.26)*	*(2.72)*	*(2.85)*	*(1.79)*	*(1.98)*

Table 1.6: Regression Analysis

Firm level Fama-Macbeth cross-sectional regression results are reported for high and low short interest stocks for the period 1988 to 2013. *Beta* refers to sensitivity of a stock to market returns; *LN(Size)* refers to natural logarithm of market capitalization of a stock; *BM* refers to ratio of book value to market value of a stock; *MOM* refers to previous 6-months returns; *RSI* refers to relative short interest; *HighRSI* refers to high short interest dummy with a value of 1 for high relative short interest stocks and 0 for relative low short interest stocks; *IO* refers to percentage of institutional ownership; *IVOL* and *ISKEW* refer to idiosyncratic volatility and idiosyncratic skewness respectively; *ILLIQ* refers to Amihud' illiquidity measure.

	1	2	3	4	5
Intercept	0.0155	0.0125	0.0189	0.0160	0.0126
	(4.18)	*(3.22)*	*(4.64)*	*(3.92)*	*(3.00)*
Beta	0.0025	0.0027	0.0027	0.0022	0.0025
	(1.16)	*(1.32)*	*(1.28)*	*(1.06)*	*(1.19)*
LN(Size)	-0.0022	-0.0029	-0.0030	-0.0022	-0.0016
	(-3.56)	*(-3.99)*	*(-3.83)*	*(-2.70)*	*(-1.96)*
BM	0.0049	0.0056	0.0048	0.0057	0.0047
	(4.92)	*(5.91)*	*(4.80)*	*(5.76)*	*(4.82)*
MOM	-0.0001	0.0003	0.0001	-0.0002	0.0007
	(-0.06)	*(0.13)*	*(0.05)*	*(-0.11)*	*(0.35)*
RSI	-0.0002				
	(-1.74)				
HighRSI		0.0136	-0.0120	-0.0024	-0.0026
		(4.72)	*(-3.24)*	*(-0.76)*	*(-0.82)*
IVOL		0.1115			
		(2.38)			
IVOL*HighRSI		-0.4602			
		(-6.95)			
IO			-0.0119		
			(-2.60)		
IO*HighRSI			0.0332		
			(6.48)		
ISKEW				-0.0007	
				(-0.82)	
ISKEW*HighRSI				0.0013	
				(1.13)	
ILLIQ					0.0001
					(3.57)
ILLIQ*HighRSI					-0.0377
					(-2.13)
Adj.-R^2	0.0614	0.0752	0.0656	0.0643	0.0744

Table 1.7: Regression Analysis for High Short Interest Stocks

Firm level Fama-Macbeth cross-sectional regression results are reported for high short interest stocks for the period 1988 to 2013. *Beta* refers to sensitivity of a stock to market returns; *LN(Size)* refers to natural logarithm of market capitalization of a stock; *BM* refers to ratio of book value to market value of a stock; *MOM* refers to previous 6-months returns; *IO* refers to percentage of institutional ownership; *IVOL* and *ISKEW* refer to idiosyncratic volatility and idiosyncratic skewness respectively; *ILLIQ* refers to Amihud' illiquidity measure.

	RSI 90%ile		***RSI 90%ile to RSI 94%ile***		***RSI 95%ile***	
	1	2	3	4	5	6
Intercept	0.0063	0.0070	0.0036	0.0012	0.0042	0.0037
	(1.03)	*(1.12)*	*(0.53)*	*(0.18)*	*(0.52)*	*(0.41)*
Beta	0.0040	0.0042	0.0059	0.0062	0.0023	0.0023
	(1.39)	*(1.47)*	*(1.91)*	*(1.99)*	*(0.76)*	*(0.76)*
LN(Size)	-0.0001	-0.0013	-0.0002	-0.0009	0.0006	-0.0005
	(-0.10)	*(-1.72)*	*(-0.24)*	*(-1.17)*	*(0.61)*	*(-0.39)*
BM	0.0038	0.0033	0.0033	0.0031	0.0055	0.0054
	(3.13)	*(2.80)*	*(2.14)*	*(2.00)*	*(3.62)*	*(3.50)*
MOM	0.0044	0.0043	0.0035	0.0038	0.0079	0.0080
	(1.47)	*(1.44)*	*(1.10)*	*(1.20)*	*(2.11)*	*(2.17)*
IVOL	-0.2532	-0.2883	-0.2009	-0.2331	-0.2726	-0.2933
	(-4.22)	*(-4.78)*	*(-2.35)*	*(-2.66)*	*(-3.72)*	*(-3.94)*
IO		0.0128		0.0123		0.0133
		(5.23)		*(4.02)*		*(4.51)*
ISKEW		0.0009		0.0004		0.0016
		(1.33)		*(0.43)*		*(1.65)*
ILLIQ		-0.0209		-0.0009		-0.0442
		(-1.21)		*(-0.03)*		*(-0.46)*
Adj.-R^2	8.09%	9.19%	9.69%	11.38%	9.39%	10.80%

Essay 2

Frictionless Short Positions and Asymmetric Risk Premium: Evidence from Futures Markets

1. Introduction

Since arbitrage is an essential element of market efficiency, limits to arbitrage may impede the ability of investors to correct mispricings (Shleifer and Vishny, 1997). One commonly cited and important example of limits to arbitrage is the difficulty in short selling that may result in security overvaluation (Miller, 1977). In this paper, we examine whether removing external constraints on short positions result in unbiased prices.

The inability of investors to short sell stocks arises from several sources. First, many institutional investors are prohibited from short selling, especially pension funds and mutual funds. Almazan et al. (2004) report that about 70% of mutual funds are prohibited from short selling, and only 3% of all mutual funds actually engage in short selling. Second, government regulations frequently restrict short-selling through the uptick rule, and locational and delivery requirements.[5] In addition, investors may be unable to borrow shares to short sell because of excessive demand, limited float, and stock illiquidity. This may cause certain stocks to have high rebate rates (D'Avolio, 2002; Geczy, Musto, and Reed, 2002). Third, the hurdle required return for short positions is higher than for long positions because short sellers must overcome the upward drift in stock prices. Fourth, risks in arbitrage exist because a stock may appreciate due to noise traders before it returns to its normal level. In particular, investor sentiment may influence prices of many stocks to move in the same direction at the same time (Kumar and Lee, 2006; Baker and Wurgler, 2006; De Long et al., 1990). Additionally, the risk of a short squeeze is high especially in stocks that are desirable candidates for short selling (Geczy, Musto, and

[5]The weaker alternative uptick rule was instituted by the SEC in 2010 (SEC, 2010a; SEC, 2010b).

Reed, 2002; Mitchell, Pulvino, and Stafford, 2002). Finally, the inherent skewness in distribution of returns and consequent right-tail risk makes short positions riskier than long positions making investors less willing to take or hold short positions (Stambaugh, Yu, and Yuan, 2013; Chen and Singal, 2003). For all of the reasons enumerated above, the level of short selling in equity markets is low (Asquith, Pathak, and Ritter, 2005) and may be suboptimal (Hong and Sraer, 2012) leading to overvaluation. Though both institutional and individual investors are reluctant to short sell, the level of short-selling among individual investors is particularly abysmal at 0.29% of shares outstanding (Barber and Odean, 2008). These frictions are not present in futures markets as there is no uptick rule or alternative uptick rule to limit opening of short positions. The costs of opening a long and short position are equal, and are related to a futures contract's volatility and commissions. Moreover, the expected return on futures contracts is zero, unlike the expected upward drift in stock prices.

The effect of various short-sale constraints on market efficiency has been evaluated extensively in the literature but with little consensus. From a theoretical standpoint, Diamond and Verrecchia (1987) argue that rational traders will adjust for expected short sale restrictions resulting in no average overpricing though returns may be skewed. However, Bai, Chang, and Wang (2006) and Cao, Zhang and Zhou (2007) find ambiguous effects of short sale constraints on stock prices when they relax some of the assumptions in Diamond and Verrecchia (1987). On the other hand, Harrison and Kreps (1978) and Duffie, Garleau and Pedersen (2002) show that, under certain circumstances, prices with unconstrained short selling may be higher than when short selling is prohibited. Duffie, Garleau, and Pedersen (2002) also show that the price effect of short selling constraints is nonlinear and affects only a small subset of stocks where demand for shortable shares outstrips supply.

The empirical literature has contributed much to our understanding of short-sales but many questions remain. First, the low level of short-selling is not explained by supply of loanable stocks or borrowing costs (D'Avolio, 2002). Second, studies generally find that short-selling is informative. However, the relationship between the intensity of short selling, as measured by short interest, and subsequent returns is weak.[6] Third, evidence related to the relationship between cost of borrowing (rebate rates) and future returns is mixed.[7] Fourth, studies exploiting cross-sectional and time-series differences in short sale constraints find that these constraints reduce liquidity and price discovery but do not lend an upward bias to prices.[8] Fifth, the effect of the uptick rule was studied by the SEC in a pilot program where they randomly suspended short-sale price tests for one-third of the Russell 3000 stocks. In studying the impact of suspension of the uptick rule, Diether, Lee and Werner (2009) and SEC (2007) found that short selling activity increases but with limited impact on market quality. Sixth, Stambaugh et al. (2012) find that higher investor sentiment is correlated with over-valuation due to arbitrage risk. Relatedly, overvaluation results in greater returns for short positions in high investor sentiment environments but returns are the same for long positions in both high and low investor sentiment environments.

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[6] See Desai et al. (2002), Asquith, Pathak, and Ritter (2005), and Boehmer, Huszar, and Jordan (2010).

[7] See D'Avolio (2002), Geczy, Musto and Reed (2002), Ofek, Richardson, and Whitelaw (2004), Jones and Lamont (2002), Boehmer, Jones, and Zhang (2008), and Banerjee and Graveline (2013). More recently, Kaplan, Moskowitz, and Sensoy (2013) report that an experiment where rebate rates were artificially changed did not result in any noticeable effect on asset prices. However, Drechsler and Drechsler (2014) find that stocks with low rebate rates do not exhibit anomalous price patterns whereas stocks with high rebate rates do. To further isolate the effect of supply constraints on prices, researchers have investigated supply shocks (loan fees in Cohen, Diether, Malloy, 2007; option introduction in Sorescu, 2000; and lockup expirations in Ofek and Richardson, 2003) but the results are not convincing according to Kaplan, Moskowitz, and Sensoy (2013).

[8] For example, studies have exploited cross-sectional differences in short sale constraints (Hong Kong stocks in Chang, Cheng, and Yu, 2007; stocks across 46 countries in Bris, Goetzmann, and Zhu, 2007) and time-series differences in short sale constraints (short selling ban on financial firms in Bris, 2008; bans around the world in Beber and Pagano, 2011). On the other hand, using a sample of Hong Kong stocks, Hwang, Liu, and Xu (2013), report that the ability to short sell improves arbitrage making prices of both overpriced and underpriced stocks less biased.

In spite of the large literature on short selling and its impact on prices, there is no study that examines the effect of short selling on asset prices in the absence of such short sale constraints. This paper, abstracts from the traditional constraints on short selling found in equity markets by focusing on short positions[9] in futures markets, where taking a short position in a futures contract is as unconstrained as taking a long position. Even with frictionless short positions, an important concern for short position holders in futures markets is the riskiness of their positions due to right skewness of return distributions.

It is in this context that we study short positions in futures markets and examine whether prices are biased or there is a risk premium associated with the short positions. Since risk management becomes more difficult when markets are closed or illiquid, we reason that futures traders will close or hedge positions with poor risk characteristics prior to periods of limited or no trading.[10] Thus, going into a weekend, we expect upward pressure on prices in assets where investors with short positions are less willing to keep their positions open and/or hedge their open positions compared with investors with long positions. We use an empirical framework for computation of risk associated with long and short positions based on historical price distributions and apply the model to futures markets. Investors in the futures markets will manage the risk of their portfolios, which will vary depending on the price distribution, current price, and the type of position (short or long). Thus, a short position in an asset where expected loss is high based on historical probabilities has an inferior risk-return tradeoff than a short position in the same asset where expected loss is low. The weekend return (Friday's return minus Monday's return) might be significantly positive if short positions are hedged ahead of the

[9] We are not equating short selling in equity markets with short positions in futures markets because the trading mechanism and motivation for these two types of trades are not same. However, futures markets provide an excellent testing ground for our hypothesis.
[10] Futures markets do not necessarily close after 'regular trading hours'; however, the hourly volume in after-market hours is less than 5% of the hourly volume in regular trading hours.

weekend and reinitiated after markets open on Mondays, especially when the risk of those positions is high. The presence of a positive weekend return might suggest a bias in prices.

Based on the most active contracts, we find that the weekend return is a statistically and economically significant 0.53% if the expected loss to short positions is more than 45%, a significant 0.37% if the expected loss is more than 35%, and a significant 0.19% if the expected loss more than 25%. In terms of individual contracts, we find that the weekend effect is the strongest for Crude oil where it is 0.94% when the expected loss to short positions exceeds 45%. On the other hand, there is no statistically significant reverse weekend effect for long positions. Moreover, the frequency of high expected losses to short positions is much higher than the occurrence of high expected losses to long positions: 492 weekends with losses of 45% or more for short positions compared with only 18 weekends for long positions over the sample period, 1990-2012. Not unexpectedly, we also find that the weekend effect is strongly correlated with the volatility of prices, which is reflected in the riskiness of short positions. However, the riskiness of long positions is not significantly correlated with the weekend, suggesting once again that the risk of short positions is the primary determinant of the weekend effect.

Finally, we examine mechanisms by which short sellers mitigate their risk over weekends. In particular, call options can hedge the risk of short futures positions, while put options can be substitutes for short futures positions. We find that changes in open interest in options markets are consistent with this expectation: open interest in both call options and put options increases on the last weekday (usually a Friday) and declines on the first weekday (usually a Monday), especially for energy futures contracts. However, we do not find a significant change in open interest in futures markets, possibly due to the high volatility of open interest in those markets.

Overall, the results are consistent with the notion that, in the absence of any explicit and known constraints on short selling, prices are unlikely to be upwardly biased. However, a weekend effect is observed due to the higher risk inherent in short positions around periods of non-trading.

The rest of the paper is organized as follows. Section 2 presents the empirical risk model used in calculating the expected loss for short and long positions, and its application to the weekend effect. Section 3 covers the data sources and sample characteristics. Section 4 discusses the results of the analysis. Section 5 contains some robustness checks and Section 6 concludes.

2. Empirical Risk Model and the Weekend Effect

There are different ways of quantifying risk of financial positions. Berkowitz and O'Brien (2002) examine several Value at Risk (VaR) approaches to evaluate the performance of trading risk models of banks and find that the GARCH model is generally better at predicting changes in volatility. Vassalou and Xing (2004) use Merton's (1974) option pricing model to calculate the distance to default and default probability for individual firms to assess the impact of default risk on equity returns. Gupta and Liang (2005) implement VaR approach to examine the risk characteristics and capital adequacy of hedge funds and find that VaR based measures perform better than traditional risk measures like standard deviation of returns and leverage ratios in capturing hedge fund risk. For our analysis, we implement an empirical risk framework that captures the risk of short and long positions[11]. We use a rolling window of two years to fit various probability distributions of price series on a weekly basis and choose the best probability

[11] We use an empirical methodology over VaR measures because our objective is to quantify the total risk (expected loss) associated with short and long positions. VaR, on the other hand, quantifies the tail risk which is not a good measure for capturing the overall risk associated with the open positions.

distribution using the Akaike information criterion (AIC; Akaike, 1974).[12] Estimates of the fitted distribution are calculated and extrapolated by calculating a partial distribution, as explained in the Appendix.

2.1 Estimation of Expected Loss in Futures Markets

This model is applied to the futures markets for computing risk associated with long and short trading positions, and for evaluating the tendency of market participants to trade. In order to estimate a price distribution, a window of 500 trading days (approximately 2 years) is employed, which is rolled over on a weekly basis. A historical 500 trading day[13] price series is constructed using the return series every Thursday (Wednesday, for long weekends) and the probability distribution with the best fit is selected as the preferred distribution. The lognormal distribution is preferred for two reasons. First, the lognormal distribution has a low AIC value across all the selected futures contracts. Second, it is a parsimonious distribution with only two parameters and has a well-defined closed form solution for its partial distribution which makes calculation of expected moments simpler. The expected loss for long and short positions and the ratio of expected loss on short positions to expected loss on long positions are calculated using weekly estimates of lognormal distribution. The explicit closed form expressions are as follows with details presented in the Appendix.

Expected percent loss for short positions:

$$\frac{g(P_o)}{P_o} = \frac{e^{\mu+\frac{1}{2}\sigma^2}\,\Phi\left(\frac{\mu+\sigma^2-lnP_o}{\sigma}\right) - P_o\left(1-\,\Phi\left(\frac{-\mu+lnP_o}{\sigma}\right)\right)}{P_o} \tag{1}$$

[12] Given a set of models for the data, we choose the one with the minimum AIC value. The AIC is preferred because it evaluates goodness of fit while minimizing the number of parameters.

[13] If a window of 60 trading days (approximately 3 months) is used to estimate the price distribution, the results are weaker suggesting that investors have a longer horizon in assessing the probability of price movements.

Expected percent loss for long positions:

$$\frac{l(P_o)}{P_o} = \frac{P_o\left(\Phi\left(\frac{-\mu + lnP_o}{\sigma}\right)\right) - e^{\mu+\frac{1}{2}\sigma^2}\left(1 - \Phi\left(\frac{\mu + \sigma^2 - lnP_o}{\sigma}\right)\right)}{P_o} \tag{2}$$

Figure 2.1 shows a representative distribution of a price series. Given today's price, expected losses can be computed by integrating price differences with their associated probabilities. The area under the density function to the right of today's price gives the probability density associated with different prices to estimate the expected loss for short positions. The probability distribution to the left of today's price is used to calculate the expected loss for long positions.

Please insert Figure 2.1 here

2.2 The Weekend Effect

Investors holding long positions or short positions are most likely to re-evaluate their risk prior to going into a long period of non-trading, the weekend. A regular weekend contains approximately 65 hours of non-trading, which is four times as long as the 17 hours of non-trading over a typical weekday[14]. As shown by Chen and Singal (2003) for short-sellers in equity markets, riskier positions are more likely to be closed or hedged prior to the weekend than at any other time during the week. We draw on the same logic to hypothesize a weekend effect in futures markets and to judge whether short or long position holders drive the weekend effect.

Prior works document the existence of a weekday effect in in equity markets and other asset markets. Gibbons and Hess (1981) find a pattern in Treasury bill returns that is the same as in equity securities. Griffiths and Winters (1995), Johnston, Kracaw, and McConnell (1991),

[14] One may argue that arguments presented in this paper are not exclusive to weekends. However, longer periods of non-trading during weekends provide a better testing ground for our hypothesis.

Jordan and Jordan (1991), Ma and Goebel (1990), and Singleton and Wingender (1994) find weekday effects in a wide variety of debt instruments including federal funds, agency-issued mortgage-backed securities, and corporate debt. Coats (1981), McFarland, Pettit, and Sung (1982), and Thatcher and Blenman (2001) find weekday effects in currency exchange rates. Ball, Torous, and Tschoegl (1982) and Ma (1986) find weekday effects in the price of gold. Yu et al. (2008) find that yen spot market has the greatest return on Thursdays and worst returns on Tuesdays and the traditional Friday and Monday returns disappear. However, Bouges et al. (2009) find no evidence of weekend effect in American depository receipts over the 1998-2004 period. Doyle and Chen (2009) report a wandering weekday effect for the 11 major stock markets they examine over the 1993-2007 period. As per our knowledge, this is the first paper to present a comprehensive analysis of weekend effect on a selected set of futures contracts across all asset classes and provide a rational explanation for its existence.

3. Data Source and Sample Characteristics

Futures contracts can be broadly divided into seven asset classes: energy futures, grains futures, softs futures, equity futures, currency futures, bond futures and metals futures.[15] To generate a representative sample, at least one futures contract is selected from each asset class, usually the contract with the highest notional value of mean open interest for the year 2012. The sample contains two energy futures contracts due to the large size of those markets. As a result, the final sample has eight futures contracts for empirical analysis in the paper: Crude oil, Heating

[15] All futures data are obtained from Quandl at http://www.quandl.com, which aggregates data from several exchanges and other producers of data.

oil, Soybeans, Sugar, S&P 500 index,[16] British Pound,[17] 10-Year Treasury note, and Gold. Information about the selected contracts (in bold) and other actively traded futures contracts is presented in Table 2.1.

Please insert Table 2.1 here

Since contracts with multiple maturities trade simultaneously, a return series is constructed using the front month contract, substituting it with the second month contract when front month contract approaches maturity. This procedure results in a return series based on contracts with the highest liquidity. Front month contracts also have a smaller term premium when compared with longer maturity contracts allowing us to abstract from the term premium and concentrate on other risks associated with trading positions (Szymanowska et al., 2014). Total open interest and total volume are calculated by summing up open interests and volumes of all active contracts for each particular day. Thus, we obtain a daily time series of returns, volumes and open interests. The final dataset consists of 6,275 daily observations for each selected futures contract.

Spot prices of the underlying assets are obtained from Quandl, whereas aggregate open interest for call and put options on selected futures contracts from 1996, the earliest available, are from Bloomberg. In addition, the average bid-ask spreads come from CME's liquidity monitor quarterly report for WTI Crude oil, mini S&P500 index[18] and 10-year Treasury note futures

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[16] Although the E-mini S&P 500 index futures contract has a higher mean notional value of open interest, the S&P 500 index futures contract is selected because the data series for E-mini S&P 500 index futures contract is shorter and does not cover our sample period. However, the underlying security for both futures contracts is the same.

[17] The British Pound futures contract is selected instead of the Yen futures contract because there is evidence of frequent intervention in the currency markets by the Bank of Japan. We do not choose the Euro futures contract because of its short history.

[18] Bid-ask spreads of mini S&P 500 index futures contracts are used as an approximation of the bid-ask spreads of S&P 500 index futures contracts because the underlying security for both futures contracts is the same.

contracts for the period from 2008 to 2013; bid-ask spreads for Soybeans and Gold futures are from 2010 to 2013.

3.1 Descriptive Statistics

Descriptive statistics for selected futures contracts are reported in Panel A of Table 2.2 for the period from 1990 to 2012. We observe that all futures contracts have positive mean and median daily returns over the sample period. The daily standard deviations for Crude oil and Heating oil are higher than for other futures contracts. Panel A also contains estimates of expected loss for short and long positions based on equations 1 and 2. We note that the mean expected loss for short positions is greater than the mean expected loss for long positions for all futures contracts except Gold and the S&P 500 index. This implies that short positions have higher risk compared to long positions for most futures contracts. Additionally, trading costs as implied by bid-ask spreads are higher for Soybeans contracts than for the remaining contracts. Higher trading costs can act as a limit to arbitrage for some commodities.

Panel B presents the daily returns for all weekdays. We note that the Monday mean returns are negative for commodities whereas the Friday returns are positive for commodities. Therefore, it is not surprising to see a large weekend effect. However, there is no weekend effect for financial futures contracts. As we discuss later, arbitrage between spot markets and futures markets can eliminate the weekend effect if no such mispricing is evident in the spot market. For other weekdays, for commodity futures, the returns are generally positive later in the week but small or negative early in the week.

Please insert Table 2.2 here

4. Results

The results are presented based on several tests. We test for the weekend effect based on the expected loss on short positions. Second, we test for the weekend effect based on expected loss on long positions. Third, the weekend effect is evaluated based on a ratio of expected loss on short positions to expected loss on long positions. Fourth, a regression framework is employed to separate the impacts of risk and volatility on the weekend effect. Finally, we explore risk mitigation strategies that may be used by short position holders.

4.1 The Weekend Effect for Short Positions

If risk affects trading behavior of market participants, then prices should change with significant changes in expected loss to traders. In particular, we expect significant price changes around weekends when traders are unable to limit their losses due to long periods of market closure. We categorize the expected loss on short positions into five groups of varying losses to test the presence of the weekend effect. To compute the weekend effect, Friday's returns are sorted based on prior Thursday's expected loss for short positions and Monday's returns are sorted based on the prior Friday's expected loss for short positions.

The first row of Table 2.3 contains aggregate results for all futures contracts from 1990-2012. The mean weekend return of 0.53% when expected loss for short position is at least 45% is both economically and statistically significant, and occurs in about 5% of all weekends. The weekend return falls but remains significant as the percent of loss decreases. At the other extreme, the weekend return is a statistically significant 0.08% when the loss is in excess of 5%, which occurs in about 40% of the weekends. This result shows that short position holders are actively managing their positions on Fridays relative to their actions on Mondays. We retest the weekend effect by dividing the weekends into periods of high, medium, and low *volatility*[19] and find that the weekend effect occurs only in periods of high *volatility* when traders with short positions have reason to be most concerned about the potential loss they might incur over the weekend. Next we select contracts with the highest expected loss for short position every week. The results in the 5th row show that those contracts also exhibit a weekend effect when the loss is more than 35%.

Among individual contracts, Crude oil futures and Heating oil futures present a strong weekend effect of 0.94% and 0.62% respectively (equivalent to annualized returns of 49% and 32%) when the expected loss for short positions is greater than 45%. We also see that the weekend effect is significant for Crude oil and Heating oil futures contracts when expected loss for short position is greater than 25% and it increases with the increase in expected loss on short positions. This finding confirms our hypothesis that short positions holders close or hedge their positions on Fridays relative to their positions on Mondays creating a weekend effect when the expected loss (or risk) for short positions is high before the weekend.[20]

Please insert Table 2.3 here

4.2 The Weekend Effect for Long Positions

A process similar to the one for short positions above is repeated for long positions. If futures traders adjust their risky long positions around the weekend, we would anticipate a negative weekend effect as a consequence of closing or hedging long positions. The results

[19] In these calculations, volatility is calculated by standardizing the standard deviation of price distributions (i.e. coefficient of variation) for the selected futures contracts. We also use GARCH (1, 1) to estimate varying volatility and observe that the impact of volatility and results associated with volatility remain almost similar. We use standardized standard deviation as a measure of volatility to maintain consistency in the definition of volatility throughout our analysis.

[20] Soybeans futures show a reverse weekend effect in the lowest loss group. As we find in section 5.4, this abnormal result is caused by seasonality in Soybeans prices around harvesting. For other futures contracts, the number of weekends when their expected loss is greater than 25% is small and the weekend returns are statistically insignificant.

reported in Table 2.4 show that the number of weekends where the long positions have an expected loss of 45% or more is only 18, compared with 492 weekends for short positions reported in Table 2.3. The first row with data aggregated for all futures contracts shows that the weekend effect is positive (instead of negative) and statistically significant at 0.32% when the expected loss is 25% or more. It is not statistically significant for any other loss percent. The individual contracts reveal a positive weekend effect for Heating oil and Soybeans, but a negative weekend effect for Sugar.

The puzzling occurrences of a positive weekend effect for risky long positions may be a consequence of risky short positions that occur concurrently: when risk is high for long positions, it is possibly high for short positions too. However, given the higher frequency of risky short positions, the short position holders dominate the market in an effort to manage their positions. Thus, the positive weekend effect in Table 2.4 may be due to short positions. The relative importance of long positions and short positions is explored in the next section.

Please insert Table 2.4 here

4.3 The Weekend Effect for Relative Expected Loss on Short Positions and Long Positions

The relative importance of short and long positions is evaluated using a ratio of expected loss on short positions to the expected loss on long positions, as shown in equation 8. The *Ratio* is divided into two groups (<1.0 and ≥ 1.0) with a *Ratio* of <1.0 (Low ratio) implying that the loss on long positions is greater than the loss on short positions and a *Ratio* of ≥ 1.0 (High ratio) implying the reverse. Based on this division, we expect the weekend effect to be positive when the *Ratio* ≥ 1.0, and zero or negative otherwise. In addition, each group is subdivided around the median into two groups. As a result, the four groups are a below median low ratio, above median low ratio, below median high ratio, and an above median high ratio.

Results for the full sample, including all futures contracts, in the first row of Table 2.5 show that the weekend effect is not statistically significant in the *Low Ratio* group, even for the below median low ratio subgroup where the risk of long positions is much greater than the risk of short positions, implying that the risk of long positions does not cause prices to alter significantly around the weekend. On the other hand, the weekend effect is statistically positive for the above median high ratio subgroup (0.11%), where the short positions are much riskier than the long positions. Looking at the individual contracts, we find that the weekend effect is significantly positive for Crude oil and Heating oil futures contracts: 0.40% per weekend for Crude oil and 0.43% per weekend for Heating oil futures contracts.[21]

If the above median high ratio subgroup is further conditioned to weekends where the expected loss on short positions is at least 25%, the results are even sharper. The last column of Table 2.5 shows that the weekend effect is 0.62% and 0.68% respectively for Crude oil and Heating oil contracts, which are much larger than the corresponding numbers in Table 2.3. Based on the results in Table 2.5, it is reasonable to conclude that the riskiness of the short positions is the primary reason for the weekend effect, and that the risk of long positions contributes little to weekend price patterns.

Please insert Table 2.5 here

4.4 Regression Analysis

Because the risk of positions depends on the volatility of asset prices, we test whether the weekend effect can be explained by volatility instead of the expected loss on short or long positions. Two regression models are estimated with the first model given by equation (3).

[21] A few other weekend effects are statistically significant but are not interesting nor consistent with the results in Tables 2.3 and 2.4.

$$Ret_t = \alpha_o + \alpha_1 Ratio_t + \alpha_2\,Volatility_t + \varepsilon_{1t} \tag{3}$$

where Ret_t refers to the weekend return, $Ratio_t$ refers to the ratio of expected loss on short positions and expected loss on long positions, and $Volatility_t$ refers to the standardized standard deviation of the asset price distribution over the prior 500-day period. Three samples are used: the full sample which contains all futures contracts; the High ratio group where ratio≥1; and the above median high ratio subgroup with the condition that expected loss on short positions is at least 25%.

The results in Panel A of Table 2.6 show that the coefficient on *Volatility* is statistically significant for all three samples. However, the coefficient on *Ratio* is statistically insignificant. As expected, these results underline the importance of volatility in the weekend effect, and that the weekend is larger when asset price volatility is high. Since volatility affects losses on long and short positions and to separate the effect of volatility on the weekend from the effect of expected loss on the weekend effect, we estimate model 4 after including these variables separately.

$$Ret_t = \beta_o + \beta_1 Loss\_on\_short\_positions_t + \beta_2 Loss\_on\_long\_positions_t + \beta_3\,Volatility_t + \varepsilon_{2t} \tag{4}$$

where $Loss\_on\_short\_positions_t$ refers to the expected loss on short positions and $Loss\_on\_long\_positions_t$ refers to the expected loss on long positions. From Panel B, we note that coefficient on $Loss\_on\_short\_positions_t$ is positive and statistically significant. However, neither of the coefficients on the other two variables are statistically significant: the coefficients on $Volatility_t$ and on $Loss\_on\_long\_positions_t$ are both statistically insignificant for all three samples. This finding supports the hypothesis that the risk of short positions is the primary cause of the weekend effect.

Please insert Table 2.6 here

4.5 Risk Management through Options

Given that short position holders are concerned about their exposure during periods of non-trading, there are at least two ways in which they can manage their risk. First, they can close their short positions on Fridays and reopen them on Mondays as has been observed in the stock market (Chen and Singal, 2003). At the same time, they could migrate to the options market and buy put options substituting their short futures positions with lower risk (Chen and Singal, 2003). Second, they could keep their futures positions open but hedge them by buying call options. If short position holders take these actions to manage risk, we will likely see a reduction in open interest in futures markets on Fridays with a subsequent increase on Mondays. Similarly, open interest in both call and put options should increase on Fridays followed by a decrease on Mondays. In results not tabulated here, we measure changes in open interest in futures markets around weekends but do not find a significant change. The statistically insignificant change could be caused by the high volatility of open interest in futures markets or because short futures positions are carried through the weekend.

The results from the options markets are more interesting. We obtain aggregate open interest options data from Bloomberg for the period 1996-2012. The open interest data are detrended using a prior 500-day moving average of open interest to remove the impact of increase in options trading over time. Extreme values are winsorized at 1st and 99th percentiles to reduce the impact of outliers. Changes in open interest in options are presented in Table 2.7, in Panel A for Fridays and in Panel B for Mondays. Panel A of Table 2.7 reveals that the open interest in both put options and call options increases significantly on Fridays for energy futures.[22] On the other hand, from Panel B, we note that the open interest in both put options and call options decreases significantly on Mondays for energy futures. The magnitude and significance of these changes seem to suggest that traders holding short futures positions trade options to manage their risk of short positions over the weekend.

Please insert Table 2.7 here

<u>4.6 Energy Futures and Other Contracts</u>

In Table 2.3, a reverse weekend effect for Soybeans futures contracts is reported. To explain the occurrence of this phenomenon, we hypothesize that it may be a result of seasonal price patterns in futures prices. Richter and Sorenson (2002) show the presence of seasonal patterns in price and volatility of Soybeans futures. They find that Soybeans futures prices are on average high in July prior to U.S. harvesting and low in November after U.S. harvesting. To take seasonality into account, we need a shorter period to estimate the price distribution, therefore, a historical 60 trading day price series (approximately 3 months) using the return series is constructed every Thursday (Wednesday, for long weekends) and lognormal distribution is fitted on the price series. The results are reported in Table 2.8 and they show that reverse weekend effect in Soybeans futures disappears but the weekend effect is still present for energy futures. This result confirms our hypothesis that a reverse weekend effect in Soybeans futures is a manifestation of seasonal price patterns.

Please insert Table 2.8 here

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[22] Soybeans move in the opposite direction consistent with evidence reported in earlier tables. As we show in section 5.4, this abnormal result is caused by seasonality in Soybeans prices around harvesting.

The analysis in Tables 2.3, 2.4, and 2.5 also shows that financial futures and Gold do not exhibit a significant weekend effect, which is contrary to the overall results and to the results pertaining to energy futures. A possible explanation for these results is arbitrage between futures and spot prices that eliminates the weekend effect in certain securities. For example, if spot markets do not exhibit a weekend effect and arbitrage between spot and futures markets is not costly, then we do not expect futures prices to exhibit a weekend effect because any mispricing in futures prices will be quickly arbitraged away. The literature on price discovery confirms that, in general, futures markets lead spot markets but results are inconclusive for currency and Treasury bonds. Kawaller, Koch and Koch (1987) examine the intraday price relationship between S&P 500 index futures and the corresponding spot index and find that futures price movements consistently lead index movements but only by twenty to forty-five minutes, which is too short to be captured by a weekend effect. Thus, arbitrage in currency, equity, and fixed income markets eliminates the possibility of a persistent weekend effect in futures prices.

On the other hand, Schwarz and Szakmary (1994) find that energy futures such as Crude oil, Heating oil and gasoline lead their respective spot markets using daily closing price data. They report that 70% and 90% of mispricing lasts until the next day for Crude oil and Heating oil futures respectively. Similarly, Yang, Bessler and Leatham (2001) document that the price discovery performance of futures contracts for storable commodities is somewhat better than for nonstorable commodities. Kim, Schwarz and Szakmary (1999) present a trading cost explanation for the relative rates of price discovery in spot and futures markets. The documented lag in arbitrage in energy markets suggests that mispriced energy prices in futures contracts can persist, which is consistent with the strong weekend effect for Crude oil and Heating oil futures contracts but not for other futures contracts.

5. Robustness Tests

In this section, we present alternative tests and explanations for the presence of a weekend effect.

5.1 Moving Average and the Weekend Effect

The weekend effect documented above should be evident when the current price is considerably different from a price trend such as a moving average. If the current price is above the moving average, there is a greater chance for the price to fall based on a historical probability distribution. Similarly, if the current price is below the moving average, there is a greater chance for the price to rise. Thus, we expect that a short position in an asset where the current price is low has an inferior risk-return tradeoff than a short position in the same asset at a higher current price. For example, if the futures price of an asset is above its 200 day moving average, then long position holders of this contract are likely to close their position before the weekend to avoid any large negative movements over the weekend, causing the price to fall. Likewise, if the futures price of an asset is substantially below its 200-day moving average, then short position holders of this contract may close their positions before the weekend, which results in an increase in the price.

To analyze the above phenomena, a price series is generated using a time series of returns. This price series is then used to calculate the 200-day moving average on a daily basis. The prices are divided into three groups: current price that is at least 10% above its 200-day moving average; current price that is at least 10% below its 200-day moving average; and where the current price is between the above two categories. Each Friday's and Monday's return is categorized into the three moving average groups based on prices on the previous Thursday and Friday.

The results are presented in Table 2.9 for the three categories. It can be observed that the weekend effect occurs only for the group where the current price is at most 90% of the 200-day moving average, that is, substantially below its moving average. The results are statistically significant for Crude oil and Heating oil futures contracts: 0.61% for Crude oil and 0.76% for Heating oil.[23] On the other hand, when the current price is at least 10% above its moving average, there is no statistically significant weekend effect, except in the case of S&P 500 index futures contracts. These results are consistent with the results reported in Tables 2.3 and 2.4.

Please insert Table 2.9 here

5.2 Basis and the Weekend Effect

If actions of short position holders around weekends cause the weekend effect, then one possibility is that the basis (the difference between the futures price and the spot price) may change over the weekend even if spot prices do not change. In this section, we measure the difference between futures prices and spot prices around the weekend.

There are two groups for each asset; one with F greater than S and the other with F less than S, where F and S refer to futures and spot prices respectively. If $F>S$, we would expect F to rise on Fridays as short sellers close or hedge their positions and for F to fall on Mondays. Thus, $F-S$ on Mondays minus $F-S$ on Fridays should be negative. Since the basis should ordinarily decrease with passage of time as a contract approaches maturity, we expect a negative change even without actions of short position holders. However, the decrease in basis should be greater when the expected loss to short positions is greater than otherwise. The exact opposite trend should be evident when $F<S$. To focus on large changes, we remove data points where the

[23] A reverse weekend effect is observed for Soybeans futures contracts. As we show in section 5.4, this abnormal result is caused by seasonality in Soybeans prices around harvesting.

absolute difference between futures and spot prices is less than its median. The sample is winsorized at the 5^{th} and 95^{th} percentiles to remove excessive impact of outliers.

Changes in basis over the weekend are reported in Table 2.10. Panel A contains the change in basis as a percent, whereas Panel B contains the change measured in dollars. Panels A and B show that, as expected, the change is generally negative and statistically significant when $F>S$ and the change is generally positive and statistically significant when $F<S$. However, the change is not greater for high loss weekends than for low loss weekends, which is contrary to our expectation. In fact, the changes across all expected loss groups seem quite close in magnitude. These results suggest that the basis does not change as a result of movement in futures prices and that the spot prices move in tandem with futures prices. This result is not surprising given that arbitrage between futures and spot markets will ensure congruence between the two prices.

Please insert Table 2.10 here

5.3 Sub-period Analysis

The weekend effect documented above is economically and statistically significant for the period 1990-2012 and we expect that it would hold its significance for sub-periods as well. In this section, we analyze whether the results are consistent across sub-periods or are concentrated in a single sub-period. The sample period is divided into four sub-periods and Friday minus Monday return is calculated in each sub-period for weekends when expected loss for short positions is greater than 35%. The results, not tabulated here, show that the weekend effect is statistically and economically significant for three out of four sub-periods which confirms that the weekend effect is consistent over time. Energy futures contracts also continue to exhibit a strong weekend effect in three out of four sub-periods.

6. Conclusion

Short selling is an important component of a well-functioning financial market because it improves informativeness of prices and enhances price discovery. However, theoretical models of short-selling are ambiguous about the impact of short selling constraints on prices, where some models (Miller, 1977) reason that these constraints introduce an upward bias in prices while Diamond and Verrecchia (1987) show that expectation of short selling constraints are reflected in prices by rational investors resulting in unbiased prices. Empirically, researchers have examined the impact of several constraints such as the uptick rule, locational requirements, rebate rates, supply of shares, and investor sentiment. Though some empirical evidence finds that short sale constraints introduce an upward bias, other evidence is generally mixed.

Because these constraints cannot be removed in equity markets, it is difficult to test whether unrestricted short selling would result in fully unbiased prices. We test the impact of frictionless short positons in futures markets where, by design, it is equally easy to take short and long positions. The only remaining distinction between short and long positions is introduced by the riskiness of those positions. Using a sample of the eight most actively traded futures contracts, though the results are most evident in energy contracts, we find that short positions are generally riskier than long positions.

Drawing on prior work that finds that investors close or hedge risky positions prior to long periods of non-trading, we reason that futures traders will also close or hedge riskier positions prior to a weekend. In this paper, we find, for the first time, a comprehensive evidence of a weekend effect in futures markets: Friday return minus Monday return is a statistically significant 0.37% when the loss on a short position is at least 35%. Moreover, the weekend effect is strongly and positively related to the expected loss on short positions. On the other hand, the risk of long positions does not result in a significant weekend effect.

In conclusion, we find that, due to the absence of external constraints on short positions in futures markets, prices are unlikely to be biased upwards. However, a weekend effect exists in the futures markets and is attributed to differential risk of short and long positions. Second, the risk premium is greater for futures contracts whose prices are more volatile, which is consistent with Doran, Jiang, and Peterson (2012) who find that high volatility stocks fall in value after short sale constraints are relaxed.

Appendix 2.A

The following expressions are implemented to calculate estimates of the fitted distribution

$$g(P_o) = E(P; P > P_o)p(P > P_o) - P_o p(P > P_o) = \int_{P_o}^{\infty}(P - P_o)f(P)dP \qquad \text{(i)}$$

where P_o is the daily closing price of an asset and $f(P)$ is the probability density function for price series. This value of $g(P_o)$ provides the expected loss associated with a short position. The expected loss associated with a long position is computed using equation (2):

$$l(P_o) = \int_{-\infty}^{P_o}(P_o - P)f(P)dP \qquad \text{(ii)}$$

Finally, the expected loss ratio, given by equation (3), defines the relative riskiness of a short position to a long position:

$$Ratio = \frac{g(P_o)}{l(P_o)} \qquad \text{(iii)}$$

We implement lognormal distribution and estimate expected loss for short and long positions along with their relative loss as follows:

Expected percent loss for short positions:

$$g(P_o) = E(P; P > P_o)p(P > P_o) - P_o p(P > P_o) = \int_{P_o}^{\infty}(P - P_o)f(P)dP$$

$$= e^{\mu+\frac{1}{2}\sigma^2}\Phi\left(\frac{\mu + \sigma^2 - lnP_o}{\sigma}\right) - P_o\left(1 - \Phi\left(\frac{-\mu + lnP_o}{\sigma}\right)\right) \qquad \text{(iv)}$$

$$\frac{g(P_o)}{P_o} = \frac{e^{\mu+\frac{1}{2}\sigma^2}\Phi\left(\frac{\mu + \sigma^2 - lnP_o}{\sigma}\right) - P_o\left(1 - \Phi\left(\frac{-\mu + lnP_o}{\sigma}\right)\right)}{P_o} \qquad \text{(v)/(1)}$$

Expected percent loss for long positions:

$$l(P_o) = \int_{-\infty}^{P_o}(P_o - P)f(P)dP = P_o\left(\Phi\left(\frac{-\mu + lnP_o}{\sigma}\right)\right) - e^{\mu+\frac{1}{2}\sigma^2}\left(1 - \Phi\left(\frac{\mu + \sigma^2 - lnP_o}{\sigma}\right)\right) \qquad \text{(vi)}$$

$$\frac{l(P_o)}{P_o} = \frac{P_o\left(\Phi\left(\frac{-\mu + lnP_o}{\sigma}\right)\right) - e^{\mu+\frac{1}{2}\sigma^2}\left(1 - \Phi\left(\frac{\mu + \sigma^2 - lnP_o}{\sigma}\right)\right)}{P_o} \qquad \text{(vii)/(2)}$$

Relative loss ratio of short positions and long positions:

$$Ratio = \frac{g(P_o)}{l(P_o)} = \frac{e^{\mu+\frac{1}{2}\sigma^2}\,\Phi\left(\frac{\mu+\sigma^2-lnP_o}{\sigma}\right) - P_o\left(1-\,\Phi\left(\frac{-\mu+lnP_o}{\sigma}\right)\right)}{P_o\left(\,\Phi\left(\frac{-\mu+lnP_o}{\sigma}\right)\right) - e^{\mu+\frac{1}{2}\sigma^2}\left(1-\,\Phi\left(\frac{\mu+\sigma^2-lnP_o}{\sigma}\right)\right)} \qquad \text{(viii)}$$

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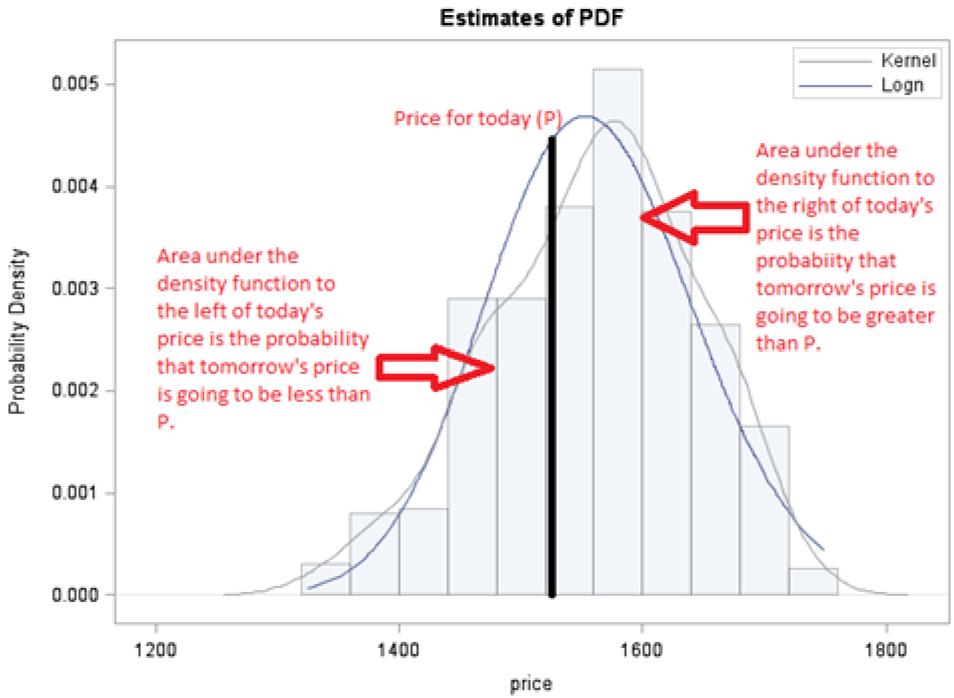

Figure 2.1: Probability Distributions

The figures show a representative distribution of a price series. Given today's price, we can calculate expected losses by integrating the price differences with its associated probabilities. The area under the density function to the right of today's price gives the probability density associated with different prices which we use to calculate expected loss for short positions. The probability distribution to the left of today's price is used to calculate expected loss for long positions.

Table 2.1: Major Futures Contracts for 2012

Mean price, mean volume, mean open interest and *notional value of mean open interest* for each futures contract for 2012 are reported. *Mean price* is the mean of daily trading value of a futures contract, quoted in dollars for energy, grains, softs, currency, and metals; quotes are in unit index for equity futures contracts; and in multiples of face value for bond futures contracts. *Mean volume* and *mean open interest* are the mean of daily volume and daily open interest respectively. *Notional value of mean open interest* is quoted in millions of dollars.

Asset Class	Asset	Contract Size	Mean Price	Mean Volume	Mean Open Interest	Notional Value of Mean Open Interest
Energy	**WTI Crude oil**	**1000 barrels**	**94.13**	**251554**	**224726**	**21037**
	Brent Crude oil	1000 barrels	111.66	197441	182522	20321
	Natural gas	10,000 m Btu	2.83	145254	147385	4147
	Heating oil	**42,000 Gallons**	**3.03**	**50535**	**62976**	**8002**
	Gasoline	42,000 Gallons	2.92	50860	63612	7814
Grains	Corn	5,000 Bushels	6.94	109348	311827	10740
	Wheat	5,000 Bushels	7.51	47130	121693	4641
	Soybeans	**5,000 Bushels**	**14.58**	**64379**	**173527**	**12805**
Softs	**Sugar**	**112,000 pounds**	**21.57**	**47960**	**248240**	**5899**
	Coffee	37,500 pounds	1.75	8424	32319	2149
	Cotton	50,000 pounds	0.80	9119	72454	2862
Equities	**S&P 500 index**	**$250 per unit index**	**1376.34**	**12229**	**214223**	**73470**
	E-mini S&P 500 index	$50 per unit index	1375.81	1611677	2666643	183333
	E-mini NASDAQ 100 index	$20 per unit index	2638.10	217566	379315	20052
	Dow Jones	$10 per unit index	12925.57	358	12767	1649
	E-mini Dow Jones	$5 per unit index	12925.35	102615	99111	6408
	Russell Small cap	$100 per unit index	804.43	110053	373703	29963
Currencies	Australian Dollar	100,000 AUD/USD	1.03	119171	150142	15496
	Canadian Dollar	100,000 CAD/USD	1.00	82295	128662	12890
	Swiss Franc	125,000 CHF/USD	1.07	35943	46626	6202
	Euro FX	125,000 EUR/USD	1.29	250623	270147	43310
	British Pound	**62,500 GBP/USD**	**1.59**	**95536**	**152690**	**15133**
	Japanese Yen	12,500,000 JPY/USD	0.01	84853	145176	22738
Bonds	2-Year Treasury note	200,000 dollars FV	110.22	129733	595052	131188
	5-Year Treasury note	100,000 dollars FV	124.02	310427	848558	105217
	10-Year Treasury note	**100,000 dollars FV**	**132.71**	**737383**	**1284069**	**170244**
	30-Year Treasury bond	100,000 dollars FV	146.49	253449	445608	65225
Metals	**Gold**	**100 troy ounces**	**1669.34**	**69098**	**83296**	**13796**
	Silver	5,000 troy ounces	31.17	19055	18995	2937
	Copper	25,000 pounds	3.61	23632	24777	2199

Table 2.2: Descriptive Statistics and Weekday Returns

Mean, median and standard deviation of daily returns and the mean of daily open interest for 1990 to 2012 are reported in Panel A. Expected losses for short and long trading positions are based on equations 1 and 2. Daily means and standard deviations of bid-ask spreads for Crude oil, S&P 500 index and Treasury notes are from 2008 to 2013, and for the others from 2010 to 2013. *N* is the total number of observations. Mean, median and standard deviation of daily returns for each weekday and the weekend return are in Panel B for 1990 to 2012.

Panel A: Descriptive Statistics

Asset	Mean Return	Median Return	Standard Deviation	Expected Loss for Short Positions		Expected Loss for Long Positions	
				Mean	Median	Mean	Median
WTI Crude oil	0.05%	0.06%	2.36%	17.58%	8.86%	11.42%	8.12%
Heating oil	0.06%	0.02%	2.25%	19.11%	7.86%	11.83%	8.43%
Soybeans	0.04%	0.04%	1.50%	12.18%	4.16%	6.80%	3.67%
Sugar	0.04%	0.00%	2.09%	17.94%	13.74%	9.99%	4.17%
S&P 500 index	0.03%	0.05%	1.20%	3.58%	0.36%	9.38%	8.29%
British Pound	0.01%	0.00%	0.62%	4.17%	2.04%	2.04%	1.30%
10-Y Treasury note	0.02%	0.02%	0.39%	3.81%	2.66%	1.44%	0.86%
Gold	0.02%	0.00%	1.03%	2.81%	1.82%	5.71%	4.65%

Panel A: Descriptive Statistics (Continued)

Asset	Mean Open Interest	Bid-Ask Spread		N
		Mean	Standard Deviation	
WTI Crude oil	708765	0.04%	0.02%	5541
Heating oil	176721	-	-	5538
Soybeans	465037	0.08%	0.03%	5569
Sugar	326681	-	-	5531
S&P 500 index	387079	0.03%	0.02%	5555
British Pound	66822	-	-	5539
10-Y Treasury note	940793	0.02%	0.01%	5543
Gold	250350	0.03%	0.01%	5540

Table 2.2

Panel B: Weekday Returns

Asset	Using Friday's Returns			Using Monday's Returns			Weekend Effect (Last Weekday-First Weekday)*		
	Mean Return	Median Return	Standard Deviation	Mean Return	Median Return	Standard Deviation	Mean Return	Median Return	Standard Deviation
WTI Crude oil	0.16%	0.19%	2.08%	-0.04%	-0.03%	2.75%	0.14%	0.28%	3.26%
Heating oil	0.02%	-0.03%	2.04%	-0.12%	-0.11%	2.61%	0.11%	0.16%	3.22%
Soybeans	0.04%	0.05%	1.60%	-0.02%	0.05%	1.77%	0.02%	0.06%	2.32%
Sugar	0.10%	0.12%	2.09%	-0.08%	-0.09%	2.26%	0.12%	0.24%	2.99%
S&P 500 index	0.00%	0.05%	1.11%	0.06%	0.08%	1.31%	-0.05%	0.02%	1.72%
British Pound	-0.02%	-0.02%	0.63%	0.00%	0.01%	0.66%	-0.02%	-0.05%	0.89%
10-Y Treasury note	0.01%	0.03%	0.45%	0.01%	0.00%	0.34%	0.00%	0.03%	0.58%
Gold	0.08%	0.04%	1.04%	-0.02%	0.00%	0.99%	0.08%	0.03%	1.46%

Asset	Using Tuesday's Returns			Using Wednesday's Returns			Using Thursday's Returns		
	Mean Return	Median Return	Standard Deviation	Mean Return	Median Return	Standard Deviation	Mean Return	Median Return	Standard Deviation
WTI Crude oil	-0.06%	-0.06%	2.14%	0.12%	0.12%	2.44%	0.12%	0.16%	2.50%
Heating oil	0.00%	-0.13%	2.05%	0.20%	0.20%	2.35%	0.21%	0.21%	2.40%
Soybeans	0.06%	0.07%	1.48%	0.07%	0.05%	1.45%	0.02%	0.00%	1.42%
Sugar	-0.02%	-0.07%	2.11%	0.15%	0.12%	2.08%	0.01%	0.00%	2.16%
S&P 500 index	0.05%	0.02%	1.22%	0.02%	0.09%	1.10%	0.00%	0.06%	1.19%
British Pound	0.02%	0.01%	0.65%	0.00%	0.00%	0.63%	0.04%	0.02%	0.60%
10-Y Treasury note	0.04%	0.03%	0.38%	0.01%	0.01%	0.38%	0.01%	0.00%	0.41%
Gold	-0.01%	0.00%	0.98%	0.02%	0.00%	0.97%	0.01%	0.00%	1.05%

**Mean return for the weekend effect differs from difference between Friday's return minus Monday's return because of the inclusion of long weekends in calculation of the weekend effect*

Table 2.3: The Weekend Effect for Short Positions (1990-2012)

Loss refers to the expected loss on short positions. *Return* is mean of Friday's return minus Monday's return and *N* is the number of weekends falling in respective loss groups. *Contracts with Maximum Loss* sample refers to the sample created by selecting contracts with maximum expected loss for every weekend. *Full sample* refers to the aggregation of all contracts. We divide the *Full sample* on the basis of standardized volatility of price series into three groups, namely *Full sample with high volatility, Full sample with medium volatility,* and *Full sample with low volatility.*

	Group	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Asset						
Full sample	Return	*0.08%	*0.13%	**0.19%	***0.37%	***0.53%
	N	3686	1976	1240	785	492
Full sample with high volatility	Return	**0.15%	**0.20%	**0.28%	***0.43%	***0.58%
	N	1949	1367	968	662	419
Full sample with medium volatility	Return	-0.01%	-0.02%	-0.10%	0.02%	0.23%
	N	1263	568	272	123	73
Full sample with low volatility	Return	0.01%	-0.05%			
	N	474	41			
Contracts with Maximum loss	Return	0.04%	0.08%	0.09%	**0.32%	**0.40%
	N	1142	946	662	483	356
WTI Crude oil	Return	0.15%	0.28%	*0.41%	**0.63%	***0.94%
	N	725	445	295	203	131
Heating oil	Return	0.15%	0.14%	*0.41%	***0.58%	***0.62%
	N	655	449	326	248	192
Soybeans	Return	**-0.19%	-0.15%	-0.27%	-0.27%	-0.10%
	N	547	327	195	115	73
Sugar	Return	0.14%	0.18%	0.09%	0.20%	0.25%
	N	741	555	372	207	92
S&P 500 index	Return	0.23%	0.15%	0.17%	0.33%	0.80%
	N	236	82	36	12	4
British Pound	Return	-0.06%	-0.04%	-0.06%		
	N	311	81	16		
10-Y Treasury note	Return	0.05%	0.00%			
	N	287	26			
Gold	Return	0.14%	1.20%			
	N	184	11			

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.4: The Weekend Effect for Long Positions (1990-2012)

Loss refers to expected loss on long positions. *Return* is the mean of Friday's return minus Monday's return and *N* is the number of weekends falling in respective loss groups. *Contracts with Maximum Loss* sample refers to the sample created by selecting contracts with maximum expected loss for every weekend. *Full sample* refers to the aggregation of all assets.

Asset	Group	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Full sample	Return	0.02%	0.04%	**0.32%	0.05%	1.39%
	N	3926	1539	579	174	18
Contracts with maximum loss	Return	0.03%	0.07%	0.23%	-0.16%	0.54%
	N	1157	801	354	122	17
WTI Crude oil	Return	0.07%	0.22%	0.23%	0.14%	0.31%
	N	718	343	169	61	14
Heating oil	Return	-0.04%	0.00%	***0.74%	***1.12%	7.18%
	N	680	422	178	50	2
Soybeans	Return	0.18%	0.26%	*0.69%	-0.32%	
	N	496	155	52	8	
Sugar	Return	0.07%	-0.16%	-0.14%	**-0.98%	3.14%
	N	538	321	174	55	2
S&P 500 index	Return	-0.10%	0.00%	-0.96%		
	N	786	249	5		
British Pound	Return	-0.01%				
	N	117				
10-Y Treasury note	Return	-0.06%				
	N	41				
Gold	Return	0.04%	-0.11%	2.42%		
	N	550	49	1		

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.5: The Weekend Effect for Relative Expected Loss on Short Positions and Long Positions (1990-2012)

Ratio refers to relative loss. The *Low Ratio* and *High Ratio* subgroups are subdivided into two groups each based on the median. Contracts where the loss on short positions >25% is selected from the *Above median high ratio group. Return* is mean of Friday's return minus Monday's return and *N* is the number of weekends falling in respective subgroups. *Full sample* refers to an aggregation of all contracts.

	Group	Ratio < 1.0 (Low Ratio)		Ratio >= 1.0 (High Ratio)		
Asset		Below Median	Above Median	Below Median	Above Median	Above Median High Ratio with Loss to Short Positions > 25%
Full sample	Return	0.05%	-0.01%	0.05%	**0.11%	**0.22%
	N	2383	2419	2268	2246	1017
WTI Crude oil	Return	0.02%	0.14%	-0.02%	**0.40%	**0.62%
	N	279	278	324	316	236
Heating oil	Return	0.22%	-0.16%	-0.06%	**0.43%	***0.68%
	N	290	297	284	283	221
Soybeans	Return	**0.32%	0.04%	-0.16%	-0.13%	-0.20%
	N	283	299	281	291	190
Sugar	Return	-0.12%	0.14%	**0.32%	0.05%	0.03%
	N	221	231	349	352	282
S&P 500 index	Return	**-0.16%	-0.09%	**0.31%	0.11%	0.17%
	N	448	458	120	128	36
British Pound	Return	-0.01%	-0.01%	0.01%	-0.08%	-0.06%
	N	262	263	334	338	16
10-Y Treasury note	Return	-0.01%	-0.06%	0.00%	0.04%	
	N	199	192	383	379	
Gold	Return	0.07%	0.06%	0.13%	0.10%	
	N	397	405	175	177	

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.6: Regression Analysis

The following models are estimated.

$$Ret_t = \alpha_o + \alpha_1 * Ratio_t + \alpha_2\, Volatility_t + \varepsilon_{1t}$$

$$Ret_t = \beta_o + \beta_1 Loss\_on\_short\_positions_t + \beta_2 * Loss\_on\_long\_positions_t + \beta_3\, Volatility_t + \varepsilon_{2t}$$

Full sample contains all contracts; *High Ratio group with ratio > 1.0* is the subsample where ratio of expected loss on short positions to long positions is greater than one; *Ratio > 1.0 subsample with Loss_on_short_positions > 25%* refers to the above median high ratio subgroup with expected loss on short positions of at least 25%

Panel A	Intercept	Ratio	Volatility	Adjusted R-Square	N
Full sample	0.03	0.01	***0.04	0.08%	9316
High Ratio group within ratio > 1.0	0.03	0.01	***0.04	0.08%	2246
Ratio > 1.0 subsample with *Loss_on_short_positions* > 25%	0.11	0.01	***0.08	0.19%	1017

Panel B	Intercept	Loss_on_short_positions	Loss_on_long_positions	Volatility	Adjusted R-Square	N
Full sample	-0.05	***0.54	0.41	0.02	0.17%	9316
High Ratio group within ratio > 1.0	-0.01	***0.54	-1.99	0.03	0.29%	2246
Ratio > 1.0 subsample with *Loss_on_short_positions* > 25%	*-0.54	***1.34	14.62	0.02	0.69%	1017

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.7

Panel A: Open Interest in Options on Fridays (1996-2012)

Loss refers to expected loss on short positions. *Total Options* refers to the sum of put and call options. The reported values represent Friday's percentage change in open interest and *N* is the number of weekends in respective groups.

	Group	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Asset						
WTI Crude oil	Put Options	**0.86%	**1.05%	*0.99%	0.92%	1.51%
	N	410	274	210	151	103
	Call Options	***0.92%	**1.03%	**1.09%	*1.10%	**1.78%
	N	410	274	210	151	103
	Total Options	***0.93%	**1.08%	**1.05%	*1.03%	*1.62%
	N	410	274	210	151	103
Heating oil	Put Options	***4.42%	***5.19%	***4.10%	***4.97%	***5.88%
	N	354	275	205	160	123
	Call Options	***3.34%	***3.98%	***2.93%	***3.55%	***4.33%
	N	354	275	205	160	123
	Total Options	***3.80%	***4.56%	***3.38%	***4.12%	***5.01%
	N	354	275	205	160	123
Soybeans	Put Options	***-3.52%	***-3.05%	***-3.39%	***-2.95%	**-3.04%
	N	407	284	187	112	72
	Call Options	***-3.10%	***-2.69%	***-3.09%	***-2.97%	**-2.94%
	N	407	284	187	112	72
	Total Options	***-3.31%	***-2.87%	***-3.24%	***-2.97%	**-2.97%
	N	407	284	187	112	72
Gold	Put Options	**-0.80%	-0.02%			
	N	135	7			
	Call Options	*-0.63%	0.42%			
	N	135	7			
	Total Options	*-0.61%	0.29%			
	N	135	7			

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.7

Panel B: Open Interest in Options on Mondays (1996-2012)

Loss refers to expected loss on short positions. *Total Options* refers to the sum of put and call options. The reported values represent Monday's percentage change in open interest and *N* is the number of weekends in respective groups.

	Group	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Asset						
WTI Crude oil	Put Options	**-0.69%	**-1.01%	**-1.10%	**-1.25%	**-1.94%
	N	410	274	210	151	103
	Call Options	**-0.67%	**-0.84%	**-1.16%	**-1.26%	**-2.11%
	N	410	274	210	151	103
	Total Options	**-0.73%	**-1.00%	**-1.16%	**-1.32%	***-2.10%
	N	410	274	210	151	103
Heating oil	Put Options	***-3.89%	***-4.78%	***-3.57%	***-4.04%	***-5.58%
	N	354	275	205	160	123
	Call Options	***-2.41%	***-3.02%	**-2.32%	*-2.51%	***-3.90%
	N	354	275	205	160	123
	Total Options	***-2.93%	***-3.68%	**-2.71%	**-3.02%	***-4.44%
	N	354	275	205	160	123
Soybeans	Put Options	***0.89%	***0.89%	***0.79%	***0.94%	**0.97%
	N	407	284	187	112	72
	Call Options	***0.82%	***0.80%	***0.78%	***0.89%	**0.95%
	N	407	284	187	112	72
	Total Options	***0.87%	***0.86%	***0.81%	***0.96%	**1.01%
	N	407	284	187	112	72
Gold	Put Options	0.01%	0.16%			
	N	135	7			
	Call Options	0.18%	0.49%			
	N	135	7			
	Total Options	0.11%	0.40%			
	N	135	7			

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.8: The Weekend Effect for Short Positions (1990-2012)

(60 Trading day Price Distribution)

Loss refers to expected loss for short positions, which is used to construct groups with increasing cut off values. *Return* is mean of Friday's return minus Monday's return and *N* is the number of weekends in respective groups.

	Group	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Asset						
WTI Crude oil	Return	0.09%	0.20%	0.49%	**1.01%	**1.40%
	N	577	305	171	98	50
Heating oil	Return	0.17%	0.24%	0.35%	*0.64%	0.37%
	N	579	342	187	82	37
Soybeans	Return	0.06%	0.08%	0.01%	0.00%	0.42%
	N	373	180	99	41	10
Sugar	Return	0.08%	0.20%	0.23%	-0.03%	-0.13%
	N	445	237	164	112	87
S&P 500 index	Return	-0.01%	0.56%	0.63%	-1.15%	1.98%
	N	244	44	12	4	1
British Pound	Return	0.12%	0.69%			
	N	132	8			
10-Y Treasury note	Return	-0.05%				
	N	86				
Gold	Return	0.11%	0.09%	0.00%	0.51%	
	N	350	142	52	14	

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.9: Moving Average and the Weekend Effect (1990-2012)

Price refers to the price of a futures contract and *MA* refers to the 200 day moving average. *Return* is mean of Friday's return minus Monday's return and *N* is the number of weekends in respective groups.

	Group	Price <= 0.9*MA	0.9*MA < Price <1.1*MA	Price >= 1.1*MA
Asset				
Full Sample	Return	***0.31%	0.02%	0.04%
	N	1215	7088	2174
WTI Crude oil	Return	***0.61%	-0.10%	0.11%
	N	292	537	498
Heating oil	Return	***0.76%	-0.04%	0.00%
	N	231	594	496
Soybeans	Return	***-0.39%	0.12%	0.14%
	N	178	826	329
Sugar	Return	0.10%	0.14%	0.14%
	N	315	606	408
S&P 500 index	Return	0.44%	-0.08%	***-0.21%
	N	109	991	219
British Pound	Return	0.06%	-0.02%	-0.07%
	N	51	1185	40
10-Y Treasury note	Return		0.01%	-0.35%
	N		1259	7
Gold	Return	0.15%	0.10%	-0.05%
	N	39	1090	177

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.10: Difference between Futures and Spot Prices (1988-2012)

Panel A: In Percent

Loss refers to expected loss on short positions. *F* refers to the futures price and *S* refers to the spot price. Reported values represent percentage change in difference of futures and spot prices over the weekend and *N* is the number of weekends in respective groups. *Full Sample* refers to an aggregation of all contracts in this table.

	Group	Loss < 0.05	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Asset							
Full sample	F > S	***-42.04%	***-40.62%	***-29.38%	***-28.11%	***-19.79%	***-21.45%
	N	1257	505	266	197	135	103
	F < S	***64.42%	***51.62%	***47.06%	***50.36%	***51.62%	***57.96%
	N	638	500	259	161	103	57
WTI Crude oil	F > S	***-53.30%	***-48.04%	***-52.25%	***-53.13%	**-39.34%	***-49.13%
	N	158	164	107	75	47	31
	F < S	***80.41%	***58.94%	***58.29%	***56.24%	***70.96%	***76.99%
	N	76	183	124	89	62	35
Heating oil	F > S	0.27%	-4.98%	-5.14%	**-7.33%	**-8.29%	*-8.23%
	N	237	181	135	112	87	71
	F < S	***36.53%	***17.59%	***20.78%	***24.87%	**21.71%	**26.50%
	N	72	87	66	47	32	21
S&P 500	F > S	***-10.30%	***-40.74%	**-43.22%	***-60.37%	-101.86%	-101.86%
	N	394	46	9	6	1	1
	F < S	***26.82%	***41.44%	***47.30%	***54.25%	24.71%	52.55%
	N	67	70	30	18	9	1
British Pound	F > S	***-108.07%	***-81.30%	**-65.82%	*-92.03%		
	N	129	50	14	4		
	F < S	***61.83%	***59.53%	***55.04%	***136.74%		
	N	281	133	38	7		
Gold	F > S	***-78.11%	***-90.51%	-219.51%			
	N	339	64	1			
	F < S	***92.87%	***99.15%	78.49%			
	N	142	27	1			

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Table 2.10

Panel B: In Dollars

	Group	Loss < 0.05	Loss >= 0.05	Loss >= 0.15	Loss >= 0.25	Loss >= 0.35	Loss >= 0.45
Asset							
WTI Crude oil	F > S	***-0.112	***-0.114	***-0.108	***-0.117	***-0.103	***-0.126
	N	158	164	107	75	47	31
	F < S	***0.172	***0.107	***0.099	***0.106	***0.152	***0.161
	N	76	183	124	89	62	35
Heating oil	F > S	-0.001	**-0.001	*-0.001	**-0.001	**-0.002	**-0.002
	N	237	181	135	112	87	71
	F < S	***0.006	***0.003	***0.003	***0.004	**0.004	**0.006
	N	72	87	66	47	32	21
S&P 500	F > S	***-0.590	***-2.028	**-2.323	***-2.980	*-5.050	*-5.050
	N	394	46	9	6	1	1
	F < S	***1.003	***1.804	***2.123	***2.540	1.470	4.220
	N	67	70	30	18	9	1
British Pound	F > S	***-0.014	***-0.011	*-0.008	*-0.011		
	N	129	50	14	4		
	F < S	***0.008	***0.009	***0.009	***0.018		
	N	281	133	38	7		
Gold	F > S	***-3.692	***-4.038	-3.100			
	N	339	64	1			
	F < S	***4.022	***4.718	9.850			
	N	142	27	1			

*Note: Statistical significance at 10%, 5% and 1% levels are denoted by *,**, and *** respectively.*

Essay 3

Stock Prices Matter

1. Introduction

In fully efficient markets, the nominal stock price should not matter and should be randomly chosen by firms. However, the average nominal stock price of U.S. stocks has remained around $30 (Weld et al., 2009) over the last several decades. Various explanations have been advanced: catering theory (Baker, Greenwood and Wurgler, 2009) where managers lower their stock price when they observe that investors overvalue low price stocks; trading cost dependence on nominal prices (Angel, 1997); signaling of inside information through stock splits (Brennan and Copeland, 1988; Asquith, Healy, and Palepu, 1989; and Ikenberry, Rankine, and Stice, 1996); and following a market norm when there is little to gain from deviating (Weld et al., 2009).

In this paper, we reexamine the primary assumption that nominal prices do not matter by focusing on preferences of firms' investor clientele. Prior research has found that individual investors prefer low price stocks (Barberis and Huang, 2008; Kumar, 2009; Boyer, Mitton and Vorkink, 2010; Boyer and Vorkink, 2014; Bali and Murray, 2013; Fernando, Krishnamurthy and Spindt, 2004; Schultz, 2000; Eraker and Ready, 2015; Bali, Cakici, and Whitelaw, 2011).[24] The low price stocks are defined by lottery-like characteristics such as high idiosyncratic volatility, high skewness, and generally small size. Researchers have found that these lottery-like characteristics are attractive to unsophisticated investors who believe that their losses are limited

[24] Barberis and Huang (2008) show preference of investors in lottery-like stocks using cumulative prospect theory. Birru and Wang (2014) find that investors over-estimate the skewness of low price stocks, especially around stock splits. Kumar and Lee (2006) also find support for investor sentiment in the formation of returns and report co-movement in stocks with high retail concentration.

due to the low stock price whereas their gains could be very large because of the potential to increase in price.

On the other hand, institutional investors prefer high price stocks and avoid investing in low price stocks (Falkenstein, 1996; Gompers and Metrick, 2001; Kumar and Lee, 2006). Prior research has found that high price stocks attract institutional investors as they tend to pay fixed brokerage commissions, regardless of share prices. Also, bid-ask spreads, as a percentage of prices, are smaller for high price stocks which further reduce transaction costs for high price stocks. Moreover, high price stocks are not preferred by noise traders which results in efficient pricing, reduction in volatility for these stocks (Brandt et al, 2010), and increase in innovation (Le and Lin, 2014). Furthermore, because of high institutional ownership (Asquith, Pathak, and Ritter, 2005), overvalued high price stocks are easy to short sell.

Thus, investors appear to categorize stocks based on nominal prices. This preference of retail investors for low price stocks causes overvaluation, resulting in future negative returns for these stocks. However, the conventional wisdom is that low price stocks are associated with high future returns (Fritzmeier, 1936; Pinches and Simon, 1972; Blume and Husic, 1973; Edmister and Greene, 1980; Goodman and Peavy, 1986; Tseng, 1988; Branch and Chang, 1990; Hwang and Lu, 2008). This confounding relationship between stock price and expected returns points to a strong possibility that nominal prices matter in stock valuation. Prior work has not documented a clear and correct relationship between stock price and future returns probably because it has confounded the size and price effects (Blume and Husic, 1973; Branch and Chang, 1990; Kumar, 2009; Birru and Wang, 2014).[25] For example, small-cap and loser stocks that earn high returns in January are also likely to be low nominal price stocks since decimation in firm size will occur

[25] A new paper (Birru and Wang, 2015) confirms the results of this paper by using accounting variables to construct a fitted price measure though it does not explicitly control for size.

concurrently with a drop in nominal price except when accompanied by reverse stock splits. The small firm effect has been extensively documented (Banz, 1981; Keim, 1983; Reinganum, 1981; Brown et al., 1983b; Lamoureux and Sanger, 1989; Fama and French, 1992; Rouwenhorst, 1999; Heston et al., 1999; Barry et al., 2001; Fu and Yang, 2010) and is also one of the factors in the Fama-French model of expected returns.[26] Therefore, the lack of distinction between low price stocks and small size stocks (Blume and Husic, 1973; Bachrach and Galai, 1979; Tseng, 1988; Brennan and Hughes, 1991; Kumar, 2009; Birru and Wang, 2014) can lead to possibly unfounded conclusions about low price stocks.

In this paper, we expand beyond the intersection of low price and low market cap stocks to the broader market for substantive implications. In particular, we segregate size and price effects and examine the relationship between stock prices and returns by explicitly controlling for size. To ensure that the results are not driven by small economically insignificant firms, we form our sample by choosing firms with market cap greater than $10 million every month using CRSP files from 1963 to 2013. These firms are categorized into residual price deciles[27], which are constructed using residual price measure obtained by orthogonalizing price with size. Returns for the highest residual price decile are compared with the returns for the lowest residual price decile. Overall, the highest residual price group earns an average of 0.51% more per month than the lowest residual price group. The outperformance is larger when 3-factor abnormal returns are considered: a statistically and economically significant 1.02% per month. Since momentum can cause winner stocks with potentially higher prices to outperform loser stocks with lower prices, we examine the impact of momentum on this return differential between high and low price stocks. As expected, controlling for momentum factor, this return differential decreases to a

[26] Fu and Yang (2010) find that the small size effect is due to omission of idiosyncratic volatility as an explanatory factor for returns. We explicitly consider idiosyncratic volatility in this paper.
[27] The results are similar if the number of subgroups is different (4, 5, or 30).

statistically significant 0.40% per month. The superior performance of high price stocks, controlled for market size, is new and has not been documented earlier.

In addition to documenting return differential between high and low price stocks, we find that high price stocks have lower beta, lower idiosyncratic volatility, lower idiosyncratic skewness, and lower Amihud's (2002) illiquidity than low price stocks. The higher idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006)[28] and higher idiosyncratic skewness (Eraker and Ready, 2015; Kumar, 2009) of low price stocks are associated with lower returns.

Using a unique dataset of actual shareholders from 2004 to 2012,[29] we confirm prior research (Kumar and Lee, 2006; Kumar, 2009) that individual shareholders prefer low price stocks: the number of individual shareholders is higher for low price stocks when compared with the number of shareholders holding high price stocks. Therefore, some firms deliberately maintain high stock prices to limit influence of speculative traders (Brandt, Brav, Graham, Kumar, 2010). Additionally, Dyl and Elliot (2006) document that, in order to increase their values, firms manage their share prices to appeal to the firm's investor base.

To examine whether investors' preferences might result in superior performance of high price stocks over low price stocks, we construct quartiles by implementing a dependent sort based on institutional ownership and residual price. We find that the return differential is highest for the lowest (or highest) institutional ownership (or retail ownership) quartile. The results are

[28] There is much debate on this counter-intuitive relationship. Malkiel and Xu (2006) follow a portfolio-based approach to minimize errors-in-variables problems and find a positive volatility-return relation. Bali and Cakici (2008) construct equal-weighted idiosyncratic volatility portfolios and find that the negative volatility premium is non-existent in these portfolios. However, Doran, Jiang, and Peterson (2008) find that the idiosyncratic volatility premium is negative even in equal-weighted portfolios if January returns are excluded. To capture time-variation in idiosyncratic volatility, some papers (Spiegel and Wang, 2005; Fu, 2009) use EGARCH type models and report a positive volatility-return relation.
On the other hand, Kapadia (2007) and Boyer, Mitton, and Vorkink (2010) show that with idiosyncratic skewness controls, the negative idiosyncratic volatility premium becomes weaker but it is still significantly negative. Frieder and Jiang (2007) document that stocks with high upside volatility only earn low returns but they also find that stocks with higher downside volatility fail to earn higher future returns.
[29] More information about the dataset is provided in section 2.

consistent with the hypothesis that it is the preference of individual shareholders for low price stocks that results in extreme negative future returns for these stocks.

This superior performance of high price stocks is subjected to various limits to arbitrage variables and results are consistent with the argument that the mispricing is highest for the stocks which are most difficult to arbitrage. Additionally, robustness tests are performed by re-estimating the returns for (i) different sub-periods and (ii) by using price cutoff of $5 since there is evidence to suggest that low price stocks earn low or negative returns (Kumar, 2009; Birru and Wang, 2013; Eraker and Ready, 2015). The results are consistent in different sub-periods and with price cutoff of $5 suggesting that they are not driven by extremely low price stocks.

We reconfirm our results in a longitudinal setting: stock splits where the stock price changes without necessarily affecting the underlying firm. When we compare the return of the 12-month period before and after the split (excluding 24 months prior to and 12 months after the split), we find a decrease of 23.33% in the annual return consistent with the notion that returns for high price pre-split stocks are higher than returns for low price post-split stocks. Similar results hold when 12-month and 36-month pre-split periods are excluded.

This paper is closely connected to the nominal price literature (Kumar, 2009; Baker et. al. 2009; Green and Hwang, 2009). Among its contributions, this paper is the first to document materiality of nominal prices in valuation after controlling for size. Furthermore, the return premium associated with high price stocks is potentially attributed to preference of firm's investor clientele. Besides outperformance of high price stocks, they are also less sensitive to market movements, display lower idiosyncratic volatility, lower idiosyncratic skewness, and lower illiquidity; and have higher shadow cost, as compared to those respectively of low price stocks.

The rest of the paper is organized as follows. Section 2 provides data sources and sample characteristics. Section 3 presents results along with robustness tests. Section 4 concludes.

2. Data Sources and Sample Characteristics

We obtain price data for all stocks traded on U.S. exchanges from the Center for Research on Security Prices (CRSP) for the period from 1963 to 2013. Only common stock firms (share codes 10, 11) are selected for analysis.[30] Delisting returns are included in the return series for all stocks and observations with missing returns within each calendar year are removed from the sample. We use the three Fama-French (1993) factors and the Carhart (1997) momentum factor from CRSP to calculate four-factor abnormal returns for portfolios.

The actual number of shareholders for each firm is obtained from a proxy advisory firm for the period 2004-2012.[31] In addition to the number of shareholders, we get quarterly data on institutional ownership from Thomson Reuters's Institutional (13-f) holdings for the period December 1980-December 2013. The total institutional holding is calculated by summing the quarterly stock holdings of all reporting institutions for each stock. Stocks without any reported institutional holdings are assumed to have zero institutional ownership. Monthly investor

[30] The share class with the highest median dollar volume is selected for stocks with multiple share classes. Though Berkshire Hathaway Inc. is removed from the sample because of its unusually high price, the results are unchanged if it is included in the sample.

[31] Only registered shareholders are reported in Compustat, 10K, and other publicly available sources. However, a large number of shares are held in street names (or broker names), which are not registered with the company. The incidence of unregistered shareholders has increased significantly as investors use the internet to manage and maintain their accounts. The database of shareholders used in this study is obtained from the largest proxy advisory firm in the U.S. Whenever a corporate proxy has to be distributed to the shareholders (usually once a year), proxy advisory firms poll all brokers and solicit names and addresses of their clients who hold shares of the company. The response rate is 95% to 99%. These data are collated by the firm and made available to the authors. Note that the true number of shareholders may be greater to the extent that a mutual fund has multiple shareholders. At the same time, the actual number of shareholders may be smaller if an investor holds the stock with more than one broker.

sentiment data are obtained from Jeff Wurgler's webpage from 1965 to 2010.[32] Finally, we get data on stock splits from CRSP to examine the impact of change in nominal prices on returns.

3. Results

3.1 Contemporaneous Correlations

To examine the confounding relationship between nominal prices and future returns, we start our analysis by examining cross-sectional correlations between following firm characteristics: price, market capitalization (size), book-to-market ratio, institutional ownership, idiosyncratic volatility, idiosyncratic skewness, and past 12-months returns. Book-to-market ratio is calculated by dividing quarterly book value with market capitalization for each stock. Institutional ownership is percentage of outstanding shares held by institutional investors. Idiosyncratic volatility and idiosyncratic skewness are the second and the third moment of residuals from Fama-French-Carhart four factor model.

Table 3.1 reports time series averages of cross-sectional correlations between the various firm characteristics which are candidates for predicting future returns. In accordance with our hypothesis, the correlation between price and size is very high i.e. 70%. This implies that the size effect might be the reason behind the positive return premium for low price stocks (Blume and Husic, 1973; Edmister and Greene, 1980; Goodman and Peavy, 1986; Tseng, 1988; Branch and Chang, 1990; Hwang and Lu, 2008). The correlation of price with institutional ownership is positive, which implies that institutional investors prefer high price stocks over low price stocks. Also, the negative correlation between price and idiosyncratic volatility is consistent with the literature where low price stocks are observed to have high idiosyncratic volatility. However,

[32] The sentiment data are truncated at year 2010. Per personal correspondence with Jeff Wurgler, the data have not been updated beyond 2010.

correlations between price and rest of the return predictors i.e. book-to-market, idiosyncratic skewness, and past 12 month returns are relatively small. Therefore, we do not expect variables other than size, idiosyncratic volatility, and institutional ownership to impact the relationship between nominal prices and future returns.

It is clear from the strong positive correlation between price and size that sorting stocks on nominal prices would not provide a conclusive and clear relationship between price and future returns. Thus, separating size from price is essential to examine the return predictability of price. In addition, size is highly correlated with institutional ownership and idiosyncratic volatility. Therefore, separating size from price would control effects of institutional ownership and idiosyncratic volatility as well.

Please insert Table 3.1 here

3.2 Returns for Groups Based on Size and Price

The literature documents a negative relationship between market capitalization and future returns (Banz, 1981; Keim, 1983; Lamoureux and Sanger, 1989; Fama and French, 1992; Rouwenhorst, 1999; Fu and Yang, 2010) and a negative relationship between nominal prices and future returns (Blume and Husic, 1973; Edmister and Greene, 1980; Goodman and Peavy, 1986; Tseng, 1988; Branch and Chang, 1990; Hwang and Lu, 2008). In this section, we re-examine these relationships for the period 1963 to 2013. In our analysis, we filter out stocks with price less than $1 and market capitalization less than $10 million to remove the impact of penny stocks and economically insignificant firms respectively. The sorting is done separately based on raw price and market capitalization at the end of June every year.

Table 3.2 reports equal-weighted portfolio means of raw and four-factor abnormal returns.[33] In Panel A of Table 3.2, sorting is done based on raw price and no clear pattern is observed in raw returns. Although high price stocks have higher four-factor abnormal returns than low price stocks, the return differential between highest and lowest price portfolio is not statistically significant. In Panel B of Table 3.2, stocks are sorted based on market capitalization (size) and a monotonic decline in raw returns with size is observed. In addition, large size stocks have a lower four-factor alpha as compared to small size stocks. However, there is no clear pattern in four-factor abnormal returns. These return patterns for price and size portfolios indicate that the real economic magnitude of the relationship between price and future returns is underestimated because of the high correlation between price and size.

Please insert Table 3.2 here

3.3 Returns for Groups Based on Residual Price

To purge the size effect, price and size are orthogonalized and the price residuals are used for analysis instead of raw prices. This methodology follows Nagel (2005) who uses it for institutional ownership. Price is orthogonalized by implementing the following regression framework in monthly cross-sectional regressions:

$$\ln\left(Price_{i,t}\right) = \alpha + \beta \ln\left(Size_{i,t}\right) + \gamma \ln(Size_{i,t})^2 + \varepsilon_{i,t} \tag{1}$$

[33] Cremers, Petajisto, and Zitzewitz (2010) document that standard Fama-French and Carhart (FFC) models produce statistically significant non-zero alphas even for passive benchmarks like S&P 500 and Russell 2000. This result is found to be driven by the disproportionate weight assigned to small size stocks. In addition to this finding, the authors suggest three remedies including value-weighting the factors, which seems to bring the FFC methodology closer to the practices of asset managers. In our paper, we calculate raw and four-factor returns by explicitly controlling for size which reduces the apparent impact of size effect. Moreover, our main focus is on the difference in abnormal returns between high and low price portfolios rather than abnormal return obtained relative to a benchmark portfolio.

where $\ln(Price_{i,t})$ and $\ln(Size_{i,t})$ refers to natural logarithm of price and size of stock i at time t. $\varepsilon_{i,t}$ refers to residual price which is used to construct residual price portfolios. The sample used for this analysis is same as that in Section 3.2 and is divided into deciles by residual price every month, and equal-weighted monthly returns for all portfolios are reported in Table 3.3. This methodology of portfolio construction creates variation in price by keeping the effect of size fixed.

The results support our hypothesis of outperformance of high price stocks over low price stocks. We note a monotonic increase in raw returns from the lowest to the highest residual price decile, with a return differential of 0.51% per month between highest and lowest residual price deciles. Similar patterns are observed for 1-factor (market), 3-factor (Fama-French factors) and 4-factor (with momentum) returns, and are presented in Figure 3.1. The 3-factor and 4-factor return differential between the highest and lowest residual price deciles are 1.02% and 0.40% per month respectively. These results indicate that high price stocks outperform low price stocks even after controlling for market, size, book-to-market, and momentum factors. In addition, this implies that results are not concentrated in extreme price portfolios and display consistency across all price portfolios.

These results provide evidence of the confounding effect of size effect in examining the relationship between price and returns. Further, this analysis documents the significance of prices in predicting future returns after controlling for other return predictors. Therefore, it is not surprising that previous research papers do not document this clear and significant relationship between price and future returns.

Please insert Table 3.3 here

Please insert Figure 3.1 here

3.4 Summary Statistics of Stylized Characteristics

Here we identify firm characteristics based on the literature that may differentiate low price and high price stocks, and may have the potential to explain differences in returns that we examine later. The firm characteristics we study are market beta, book to market ratio, idiosyncratic volatility, idiosyncratic skewness, liquidity, number of shareholders, Merton (1987)'s shadow cost, number of institutions, and institutional ownership.

The computation of these characteristics follows the literature: beta is estimated by implementing a rolling regression of a firm's returns for preceding 36 months on corresponding market's return; the ratio of book value to market capitalization is calculated as the average of quarterly ratios of book to market value; idiosyncratic volatility is estimated as described above in the robustness section; idiosyncratic skewness is measured as the third moment of residuals from a four-factor model for each month; and liquidity is based on Amihud's (2002) illiquidity measure[34]; number of shareholders and number of institutions is obtained directly from the databases; and percent of institutional ownership is calculated as the ratio of number of shares held by institutions and the number of shares outstanding. Finally, Merton's (1987) shadow cost of incomplete information is constructed using the methodology presented in Chen, Noronha, and Singal (2004) as below:

$$Shadow\ Cost = \frac{Market\ Cap\ of\ firm\ \times Residual\ standard\ deviation}{Market\ Cap\ of\ Top\ 3000\ stocks\ \times Number\ of\ Shareholders} \qquad (2)$$

where market cap of firm and market cap of the largest 3,000 stocks are as of the prior November, number of shareholders is measured in the prior year, and residual standard deviation

[34] Amihud's illiquidity measure is defined as average ratio of the daily absolute return to the (dollar) trading volume on that day.

is measured as the standard deviation of the difference between firm's return and the combined total return of the largest 3,000 firms in the 250-day period in the prior year.

Table 3.4 reports these characteristics following the same residual price portfolio construction as implemented in section 3.3. We observe that residual price is highly correlated with raw price as there is a clear monotonic increase in raw price from the lowest to the highest residual price portfolio. We observe that low price stocks are almost 100% more sensitive to market movements than high price stocks. The lower returns for low price stocks with higher beta are consistent with Frazzini and Pedersen (2014) who find that constrained investors cause high-beta stocks to become overvalued. Additionally, on average, there is no appreciable difference in book to market ratio for low price stocks and high price stocks. Prior research has found that low price stocks have higher idiosyncratic volatility (Brandt, Brav, Graham, and Kumar, 2010) whereas high price stocks have low idiosyncratic volatility. Our results confirm this finding: even after controlling for size, low price stocks have 111% higher idiosyncratic volatility than high price stocks. In addition to idiosyncratic volatility, idiosyncratic skewness is higher for low price stocks and it decreases as we move from the lowest to the highest residual price decile. This result is consistent with the lottery stocks literature (Kumar, 2009; Birru and Wang, 2014) where low price stocks display high skewness and negative future returns.

Consistent with Amihud (2002), we find that impact of illiquidity is more pronounced for low price stocks. In addition, high price stocks tend to be less illiquid than low price stocks. This implies that illiquidity premium is higher for low price stocks than that for high price stocks which further strengthens our results and signify that the outperformance of high price stocks over low price stocks is not driven by liquidity. Furthermore, we find that the number of shareholders is almost seven times higher for low price stocks than for high price stocks which suggests that low price stocks are preferred by individual investors, consistent with Kumar and Lee (2006) and Kumar (2009), and less preferred by institutions. This preference of low price stocks by individual investors might increase the intensity of noise trading and result in increase in volatility of low price stocks. The difference in idiosyncratic volatility between high and low price stocks, as documented above, is consistent with this prediction. In addition, the increase in the number of shareholders with size decile implies that larger firms have more shareholders than smaller firms. Merton's shadow cost, as calculated above, is winsorized at the 1%ile and the 99%ile to remove outliers. In Merton's model, if only a subset of stocks is known to some investors and they hold only those stocks, then these undiversified investors would demand a premium for their nonsystematic risk. Though the reported shadow cost is more than double for high price stocks as compared to that of low price stocks, however, in unreported results, we do not find strong support for the investor recognition hypothesis which may be due to the limited availability of shareholder data. Furthermore, we do not find much variation in size and institutional ownership between highest and lowest residual price portfolios. This result is in line with the reasoning that controlling for size provides a control for institutional ownership as well.

Please insert Table 3.4 here

3.5 Institutional Ownership and Residual Price

One of the primary motivations of this paper is the impact of preferences of firms' investor clientele on future returns. Specifically, as mentioned in the introduction, individual investors prefer low price stocks (Barberis and Huang, 2008; Kumar, 2009; Boyer, Mitton and Vorkink, 2010; Boyer and Vorkink, 2014; Eraker and Ready, 2015; Bali, Cakici, and Whitelaw, 2011) and institutional investors prefer high price stocks and avoid investing in low price stocks (Falkenstein, 1996; Gompers and Metrick, 2001; Kumar and Lee, 2006). This preference of unsophisticated investors might result in overvaluation for low price stocks. Therefore, we expect to find negative returns for stocks with low institutional ownership and low price. Moreover, the return differential between the highest and the lowest residual price portfolio would be highest for stocks with low institutional ownership as it is a constraint for short sellers (Nagel, 2005; Asquith et. al. 2005). To test this hypothesis, we divide the whole sample into quartiles based on institutional ownership and construct residual price quartiles within each institutional ownership quartile at the end of each month.

Table 3.5 reports the raw and four-factor abnormal returns in Panel A and Panel B respectively. We note that stocks in the intersection of lowest institutional ownership quartile and residual price quartile display highest negative raw (-0.74%) and four-factor (-1.71%) abnormal returns. Additionally, the raw (1.64% per month) and four-factor (1.60% per month) return differential between the highest and lowest residual price portfolio are the highest for lowest institutional ownership quartile. These results confirm our hypothesis that the preference of retail investors for low price stocks contributes to the positive return differential between high and low price stocks.

Please insert Table 3.5 here

3.6 Limits to Arbitrage and Residual Price

In the previous section, we document that investors' preference contributes to the outperformance of high price stocks over low price stocks. Therefore, it would be interesting to ascertain whether this mispricing is greatest for stocks which are difficult to arbitrage. The existing literature relies on firm characteristics, such as idiosyncratic volatility (Pontiff, 2006), illiquidity (Amihud, 2002), idiosyncratic skewness, as proxies for limits to arbitrage.

Beginning most explicitly with Ang et al. (2006, 2009), there is increasing acceptance that there may be a negative relationship between idiosyncratic volatility and returns in spite of the challenges and rational explanations for these results (Spiegel and Wang, 2005; Fu, 2009; Malkiel and Xu, 2006; Bali and Cakici, 2008; Doran, Jiang, and Peterson, 2008; Bhootra and Hur, 2015; Chichernea Ferguson, and Kassa, 2015). Idiosyncratic volatility is calculated as standard deviation of the residuals using the four-factor model for November of the year prior to that of return calculation. To avoid stocks with infrequent trading and following (Fu, 2009), stocks with at least 15 trading days in a month are selected for the analysis. Quartiles are constructed by implementing a sequential dependent sort on idiosyncratic volatility and residual price at the end of every month. Panel A of Table 3.6 reports the equal weighted raw and four-factor abnormal returns for all idiosyncratic volatility quartiles. The raw and four-factor return differentials for the highest idiosyncratic volatility portfolio are 0.91% and 0.63% respectively.

Panel B and Panel C of Table 3.6 report returns for portfolios based on idiosyncratic skewness and illiquidity respectively. In Panel B, Quartiles are constructed by implementing a sequential dependent sort on idiosyncratic skewness and residual price at the end of every month. We observe a monotonic increase in the return differential from the lowest to the highest idiosyncratic skewness quartile. Similarly, in Panel C, portfolios are formed based on dependent sort on illiquidity and residual price. A similar monotonic pattern in raw and four-factor abnormal return is observed for these portfolios. These results confirm our hypothesis that mispricing is largest for stocks with the greatest limits to arbitrage.

Please insert Table 3.6 here

3.7 Regression Analysis

In this section, we attempt to observe the return differential using different limits to arbitrage variables identified above. As in prior analyses, the sample is divided into 10 residual price deciles and firms in the highest and lowest residual price deciles are considered for the analysis. Since institutional ownership data are available starting from 1980, we restrict the regression analyses to the period from 1980 to 2013. First, we analyze the relationship between returns and price at the firm level, followed by idiosyncratic volatility (Ang et al., 2006, 2009), and idiosyncratic skewness (Mitton and Vorkink, 2007; Kapadia, 2007). Moreover, if institutional ownership is at least partly responsible for the excess return difference between high and low price stocks, we should observe a positive return differential for the interaction between percentage of institutional ownership and residual price dummy. Other explanatory variables include illiquidity, beta, size and book-to-market. We specify the following Fama-Macbeth (1973) regression framework to test the impact of these factors on returns

$$R_{i,t} = \beta_{0,t} + \sum_{k} \beta_{k,t} X_{i,t-1,k} + \varepsilon_{i,t} \qquad (3)$$

where $R_{i,j}$ refers to the average monthly raw return for firm i in year t and $X_{i,t-1,k}$ refers to explanatory variables including the high residual price dummy (D_{RP}) for different firms.

The results of time series average of firm-level Fama-Macbeth (1973) cross-sectional regressions with raw returns as the dependent variable are reported in Table 3.7. Controlling for four known factors, the coefficient on D_{RP} is positive and statistically significant. The coefficient remains significant in all the regression models expect when idiosyncratic volatility is included. Idiosyncratic volatility has a significant negative effect on returns. With idiosyncratic volatility, the coefficient of the interaction between idiosyncratic volatility and high price dummy is positive and significant. This implies that for a fixed level of idiosyncratic volatility, high price stocks outperform low price stocks. The effect of institutional ownership on abnormal returns is positive and statistically significant. We interact (1-*IO*) with D_{RP} because price and institutional ownership are negatively correlated. The coefficient of this interaction term is positive implying that keeping level of institutional ownership fixed, high price stocks outperform low price stocks. These results confirm results presented in Table 3.6 where return differentials increases with limits to arbitrage variables.

Please insert Table 3.7 here

3.8 Robustness Analysis

We evaluate the results for robustness by presenting two additional analyses: sub-period analysis (ii) excluding firms with prices less than$5.

3.8.1 Sub-period Analysis

To test the consistency of the main results presented above across the entire sample period of 51 years, a sub-period analysis is performed. The sample period is divided into two equal sub-periods i.e. from 1963 to 1987 and from 1988 to 2013. The residual price portfolios are constructed at the end of every month and equal-weighted returns are calculated. Panel A and Panel B of Table 3.8 report the raw returns, along with 1-factor, 3-factor and 4-factor abnormal returns for the sample periods 1963-1987 and 1988-2013 respectively. We find that high price stocks statistically and economically significantly outperform low price stocks in both the sample period with higher return differentials in the earlier sub-period. This analysis shows that the outperformance of high price stocks relative to low price stocks is economically and statistically significant during different sample periods.

3.8.2 Returns with Price Cut-Off

In the main analysis, the selected sample could include firms with a nominal price of less than \$5. Some may argue that the underperformance of low price stocks is concentrated in very low price stocks and may be responsible for the reported results. In this section, we use price cut off of \$5. As before, we select the entire sample and impose the price cutoff of \$5 before creating the residual price portfolios. Residual price portfolios are constructed using the same procedure as used for Table 3.3.

Summary results of this analysis are reported in Panel C of Table 3.8. The return differences with price-cutoffs of \$5 between highest and lowest price decile are smaller in magnitude but similar to the return differences without price cutoffs reported in Table 3.3. We note that high price stocks outperform low price stocks by a significant 0.36% per month when stocks with price greater than \$5 are selected, which is smaller than the return differences for stocks without any price cut-offs. These differences in raw and abnormal returns are expected because of the underperformance of stocks with prices between \$1 and \$5. These results show that the price cutoffs do not materially affect the main results of the paper.

Please insert Table 3.8 here

3.9 Sentiment Analysis

Baker and Wurgler (2006) document the impact of investor sentiment on the cross-section of stock returns and argue that sentiment exerts a stronger impact on stocks that are difficult to value and hard to arbitrage. They construct a parsimonious sentiment indicator based on the first principal component of six sentiment proxies. The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. We utilize this composite sentiment indicator to test its impact on high and low price stocks. The sample period is divided into periods of low and high sentiments based on previous month's relative sentiment. A high (low) sentiment period is defined as one in which the sentiment index in the previous month is above (below) the median value for the entire sample period.[35] Table 3.9 reports returns for high and low price portfolios along with their return differential following low and high sentiment periods. We observe that impact of sentiment is higher on low price stocks, for which average return varies from a statistically significant 1.55% following low sentiment periods to an insignificant 0.31% following high sentiment periods. However, high price stocks are less affected by market sentiment as they display only a minor change in average return: from 1.30% to 1.29% following low to high sentiment periods.

High sentiment – high price stocks strongly outperform high sentiment – low price stocks indicating that sentiment plays a significant role in driving returns and that investors are more likely to bid up the values of low price stocks. The raw and four-factor return differentials are 0.98% and 0.51% respectively following high sentiment periods. For low sentiment periods, where individual investors are less active, low sentiment – low price stocks slightly outperform low sentiment – high price stocks sentiment. However, the difference in four-factor abnormal returns is not economically or statistically significant.

These results are consistent with results in Stambaugh, Yu, and Yuan (2012), where they examine the impact of sentiment on 11 anomalies and document those anomalies are stronger following periods of high sentiment. Furthermore, our results follow their finding that the short legs (low price stocks, in our study) of these 11 anomalies are sensitive to this factor while long legs (high price stocks) are not.

[35] We follow Stambaugh, Yu, and Yuan (2012) to classify high and low sentiment periods.

Please insert Table 3.9 here

3.10 Stock Splits

The prior analysis implicitly assumes a characteristic similarity between high price stocks and low price stocks. As in the literature (for example, Green and Hwang, 2009), we use stock splits as an alternate experiment in a longitudinal setting where there is an unnatural drop in price without a fundamental change in the firm. If the lower price attracts more investors who overvalue the firm, we anticipate a decline in post-split returns.

The analysis is based on stocks with a split ratio greater than 1.5 from 1963 to 2013. The final sample consists of 8,921 stock splits. Table 3.10 documents differences in raw and market-adjusted returns along with return differences before and after the split. For each firm, pre-split returns are calculated for four 12-months periods: [-1,-12], [-13,-24], [-25,-36], [-37,-48] where [-1,-12] refers to the period from month 1 to month 12 (both included) before the month of split. In addition to pre-split returns, post-split returns are calculated for two 12-months periods: [1, 12] and [13, 24] to test whether the return differential exists before and after the split. We note that pre-split returns exceed post-split returns by 75.64% when returns are compared just before and after the month of split. However, this return difference may be a manifestation of a run up in the price of a stock in the year before the split. Therefore, we compare returns two, three, and four years before the split with returns two years after the split. We find that pre-split returns are consistently greater than post-split returns: by 31.60%, 23.33%, and 15.49% depending on comparison periods. The return differences are largely unaffected when controlled for the market. The result implies that returns fall after a stock split concurrent with a decrease in price. Assuming firm characteristics are largely unaffected by a stock split, the result supports the superior performance of high price stocks relative to low price stocks.

Please insert Table 3.10 here

4. Conclusion

We document that nominal prices matter for stock returns which potentially is a result of institutional investors' preference for high price stocks and individual investors' preference for low price stocks. When explicitly controlled for size, we find that returns to high price stocks are significantly higher than returns to low price stocks: by an abnormal 0.40% per month over the 1963-2013 sample period. The results are robust to alternate price cut-offs and when directly controlled for investor sentiment, momentum, idiosyncratic volatility, and size. Finally, we also find support for these results around stock splits: the returns fall after stock splits even when multiple years of pre-split returns are excluded.

In addition to the return differential between high and low price stocks, we find differences in various characteristics between high and low price stocks. Specifically, high price stocks display lower sensitivity to market (beta), lower idiosyncratic volatility, lower idiosyncratic skewness, and higher Merton's shadow cost than those respectively of low price stocks. We evaluate the return differential in the presence of various limits to arbitrage variables and find that this mispricing is highest for those stocks which are most difficult to arbitrage. Overall, the price effect continues to remain important. Perhaps, there is a rational explanation for firms to avoid lower prices for their stock.

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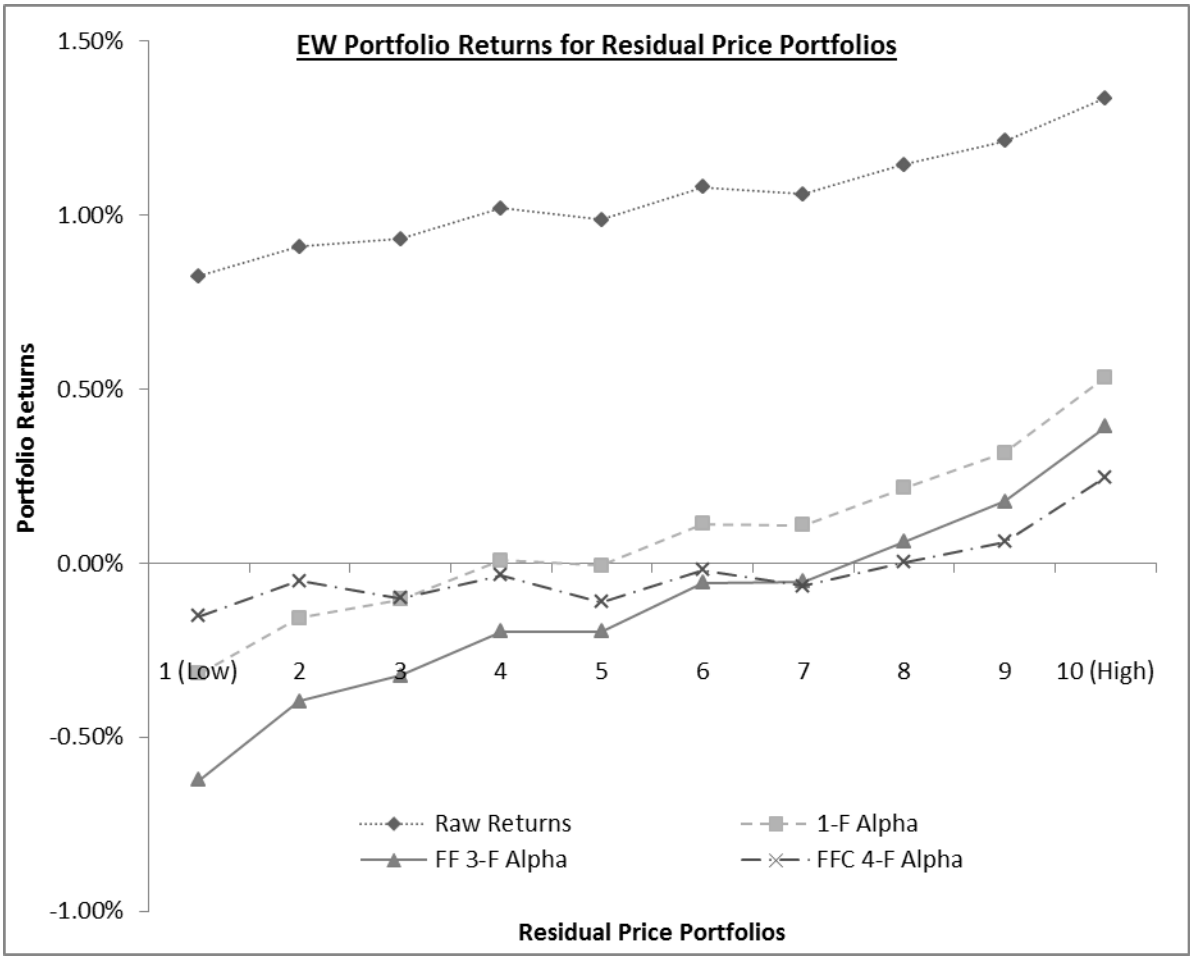

Figure 3.1: Portfolio Returns for Residual Price Portfolios

Equal-weighted monthly portfolio returns are presented based on residual price (RP) for the period 1963-2013. *1-F Alpha* refers to the intercept of portfolio returns on the excess market returns; *FF 3-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors; *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor.

Table 3.1: Contemporaneous Correlations

Time series averages of the cross-sectional correlations are reported for the period 1963 - 2013. *BM* refers to book-to-market ratio*; IO* refers to institutional ownership i.e. the fraction of shares held by institutional investors; *ISKEW* refers to idiosyncratic skewness; *IVOL* refers to idiosyncratic volatility; *RET12* refers to the buy-and-hold individual stock return over the previous 12 months; *LN(Size)* refers to natural logarithm of market capitalization; and *LN(Price)* refers to natural logarithm of price.

	LN(Price)	**LN(Size)**	**BM**	**IO**	**ISKEW**	**IVOL**	**RET12**
LN(Price)	1.00						
LN(Size)	**0.70**	1.00					
BM	-0.12	-0.15	1.00				
IO	0.29	0.33	0.27	1.00			
ISKEW	-0.04	-0.05	-0.02	-0.03	1.00		
IVOL	-0.50	-0.38	-0.02	-0.15	0.16	1.00	
RET12	0.14	0.03	-0.14	-0.02	0.00	-0.01	1.00

Table 3.2: Returns for Groups Based on Size and Price

Equal-weighted monthly portfolio returns along with their t-statistics are reported based on size and price in Panel A and Panel B respectively for the period 1963-2013. *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor. In Panel A, *Large-Small* refers to return difference between largest and smallest size decile. In Panel B, *High-Low* refers to return difference between highest and lowest price decile.

Panel A			***Panel B***		
Price Groups	**Raw Returns**	**FFC 4-F Alpha**	**Size Groups**	**Raw Returns**	**FFC 4-F Alpha**
1 (Low)	1.10%	0.00%	**1 (Small)**	1.22%	0.15%
	(5.16)	*(-0.02)*		*(7.99)*	*(1.82)*
2	1.09%	-0.02%	**2**	1.18%	0.08%
	(6.21)	*(-0.19)*		*(7.71)*	*(1.10)*
3	0.99%	-0.07%	**3**	1.09%	0.00%
	(6.26)	*(-1.18)*		*(7.20)*	*(0.02)*
4	1.11%	0.04%	**4**	1.07%	-0.07%
	(7.79)	*(0.90)*		*(7.13)*	*(-1.37)*
5	1.14%	0.06%	**5**	1.12%	-0.01%
	(8.65)	*(1.63)*		*(7.26)*	*(-0.20)*
6	1.14%	0.09%	**6**	1.04%	-0.04%
	(8.96)	*(2.77)*		*(7.19)*	*(-1.04)*
7	1.12%	0.07%	**7**	1.09%	0.05%
	(9.12)	*(2.20)*		*(7.74)*	*(1.32)*
8	1.09%	0.06%	**8**	1.08%	0.08%
	(9.20)	*(1.68)*		*(7.92)*	*(2.10)*
9	1.09%	0.10%	**9**	1.08%	0.13%
	(9.37)	*(3.07)*		*(8.59)*	*(3.67)*
10 (High)	1.05%	0.15%	**10 (Large)**	0.93%	0.08%
	(8.86)	*(3.71)*		*(8.19)*	*(2.83)*
High - Low	-0.05%	0.15%	**Large - Small**	-0.29%***	-0.07%
	(-0.32)	*(1.21)*		*(-2.50)*	*(-0.75)*

Table 3.3: Returns for Groups Based on Residual Price

Equal-weighted monthly portfolio returns along with their t-statistics are reported based on residual price (*RP*) for the period 1963-2013. *1-F Alpha* refers to the intercept of portfolio returns on the excess market returns; *FF 3-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors; *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor. *High-Low* refers to return difference between highest and lowest price decile.

RP Groups	**Raw Returns**	**1-F Alpha**	**FF 3-F Alpha**	**FFC 4-F Alpha**
1 (Low)	0.83%	-0.32%	-0.62%	-0.15%
	(4.08)	*(-2.36)*	*(-5.89)*	*(-1.58)*
2	0.91%	-0.16%	-0.40%	-0.05%
	(5.58)	*(-1.75)*	*(-6.11)*	*(-0.91)*
3	0.93%	-0.10%	-0.32%	-0.10%
	(6.29)	*(-1.44)*	*(-6.85)*	*(-2.38)*
4	1.02%	0.01%	-0.20%	-0.04%
	(7.28)	*(0.14)*	*(-4.96)*	*(-0.96)*
5	0.99%	-0.01%	-0.20%	-0.11%
	(7.37)	*(-0.09)*	*(-5.75)*	*(-3.29)*
6	1.08%	0.11%	-0.06%	-0.02%
	(8.42)	*(2.01)*	*(-1.79)*	*(-0.58)*
7	1.06%	0.11%	-0.05%	-0.07%
	(8.52)	*(1.99)*	*(-1.73)*	*(-2.11)*
8	1.15%	0.22%	0.06%	0.00%
	(9.50)	*(3.92)*	*(1.89)*	*(0.08)*
9	1.21%	0.32%	0.18%	0.06%
	(10.57)	*(5.69)*	*(5.03)*	*(1.82)*
10 (High)	1.34%	0.53%	0.39%	0.25%
	(13.39)	*(9.13)*	*(9.00)*	*(5.91)*
High - Low	0.51%***	0.85%***	1.02%***	0.40%***
	(3.49)	*(6.58)*	*(8.23)*	*(3.71)*

Table 3.4: Residual Price and Firm Characteristics

Portfolio means of Price, market beta (*Beta*), book-to-market ratio (*BM*), market capitalization (*Size*), idiosyncratic volatility (*IVOL*), idiosyncratic skewness (*ISKEW*), and illiquidity (*ILLIQ*) are reported for the period 1963-2013. Number of Shareholders and Shadow Cost are reported for the period 2004-2013. Institutional Ownership (*IO*) is reported for the period 1980-2013. *Beta* refers to sensitivity of a stock to market returns; *BM* refers to ratio of book value to market value of a stock; *IVOL* and *ISKEW* refer to second and third moment respectively of residuals from Fama-French-Carhart four-factor model; *ILLIQ* refers to the Amihud's Illiquidity measure; *Shadow Cost* refers to the Merton's shadow cost; *IO* refers to the percentage of outstanding shares owned by the Institutions. Portfolios are formed based on residual price (*RP*) at the end of each month for respective sample periods for each characteristic.

RP Groups	Price	Beta	BM	Size	IO	IVOL	ISKEW	ILLIQ	Shadow Cost	Number of Shareholders
1 (Low)	5.01	1.49	0.96	1137.73	33.4%	3.8%	25.4%	3.16	0.90	149341
2	9.68	1.33	0.89	1594.18	39.8%	3.0%	21.9%	2.43	1.20	99663
3	13.12	1.26	0.86	1697.1	41.6%	2.7%	19.7%	1.91	1.43	71520
4	16.22	1.21	0.81	2006.61	44.0%	2.5%	18.2%	1.55	1.29	127802
5	19.09	1.15	0.79	1967.82	45.3%	2.3%	16.9%	1.46	1.63	164868
6	21.74	1.11	0.80	1794.15	46.3%	2.2%	15.9%	1.33	2.11	142704
7	24.36	1.05	0.77	1507.47	46.1%	2.1%	15.4%	1.51	2.23	127048
8	27.33	1.00	0.77	1259.21	45.5%	2.0%	15.2%	1.43	2.28	93076
9	30.97	0.93	0.81	1052.63	42.7%	1.9%	15.4%	1.72	2.22	34318
10 (High)	132.37	0.73	0.99	882.53	36.4%	1.8%	16.7%	2.54	2.48	20726

Table 3.5: Institutional Ownership and Residual Price

Equal-weighted monthly portfolio returns along with their t-statistics are reported based on dependent sort of institutional ownership (*IO*) and residual price (*RP*) for the period 1963-2013. *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor. *High RP - Low RP* refers to return difference between highest and lowest residual price decile.

Panel A: Raw Returns

IO Groups	**Low RP**	**High RP**	**High RP - Low RP**
1 (Low)	-0.74%	0.89%	1.64%
	(-3.24)	*(7.80)*	*(9.83)*
2	-0.28%	0.93%	1.21%
	(-1.22)	*(7.90)*	*(7.26)*
3	1.31%	1.04%	-0.27%
	(6.11)	*(7.59)*	*(-2.04)*
4 (High)	3.97%	2.54%	-1.43%
	(15.45)	*(16.11)*	*(-8.52)*

Panel B: FFC 4-F Alpha

IO Groups	**Low RP**	**High RP**	**High RP - Low RP**
1 (Low)	-1.71%	-0.11%	1.60%
	(-13.62)	*(-1.78)*	*(12.59)*
2	-1.31%	-0.13%	1.18%
	(-10.95)	*(-2.07)*	*(9.39)*
3	0.20%	-0.13%	-0.33%
	(2.36)	*(-2.74)*	*(-3.38)*
4 (High)	3.00%	1.35%	-1.65%
	(23.74)	*(22.49)*	*(-13.76)*

Table 3.6: Limits to Arbitrage and Residual Price

Equal-weighted monthly portfolio returns along with their t-statistics are reported based on dependent sort of arbitrage variable and residual price (*RP*) for the period 1963-2013. *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor. *High RP - Low RP* refers to return difference between highest and lowest residual price decile. Panel A reports portfolio returns based on dependent sort of idiosyncratic volatility and residual price; Panel B reports portfolio returns based on dependent sort of idiosyncratic skewness and residual price; Panel C reports portfolio returns based on dependent sort of illiquidity and residual price.

Panel A: Idiosyncratic Volatility (IVOL)

	Raw Returns			***FFC 4-F Alpha***		
IVOL Groups	**Low RP**	**High RP**	**High RP - Low RP**	**Low RP**	**High RP**	**High RP - Low RP**
1 (Low)	0.94%	1.16%	0.22%	0.09%	0.28%	0.19%
	(9.45)	*(13.45)*	*(3.93)*	*(2.35)*	*(6.46)*	*(3.73)*
2	1.02%	1.30%	0.28%	0.18%	0.30%	0.12%
	(7.34)	*(11.59)*	*(3.89)*	*(3.74)*	*(6.59)*	*(1.96)*
3	0.89%	1.17%	0.28%	0.13%	0.13%	0.01%
	(4.92)	*(8.23)*	*(2.91)*	*(1.9)*	*(2.55)*	*(0.09)*
4 (High)	-0.47%	0.43%	0.91%	-1.15%	-0.52%	0.63%
	(-2.10)	*(2.55)*	*(6.80)*	*(-10.04)*	*(-7.61)*	*(5.17)*

Panel B: Idiosyncratic Skewness(ISKEW)

	Raw Returns			***FFC 4-F Alpha***		
ISKEW Groups	**Low RP**	**High RP**	**High RP - Low RP**	**Low RP**	**High RP**	**High RP - Low RP**
1 (Low)	1.03%	1.18%	0.15%	0.08%	0.09%	0.01%
	(6.01)	*(11.00)*	*(1.37)*	*(1.05)*	*(2.06)*	*(0.14)*
2	0.98%	1.32%	0.34%	-0.02%	0.18%	0.19%
	(5.60)	*(11.65)*	*(3.13)*	*(-0.21)*	*(4.11)*	*(2.20)*
3	0.94%	1.27%	0.33%	-0.01%	0.10%	0.12%
	(5.18)	*(10.97)*	*(2.82)*	*(-0.14)*	*(2.44)*	*(1.26)*
4 (High)	0.57%	1.27%	0.70%	-0.44%	0.15%	0.59%
	(3.00)	*(11.29)*	*(5.62)*	*(-5.14)*	*(3.30)*	*(6.04)*

Panel C: Illiquidity (ILLIQ)						
	Raw Returns			***FFC 4-F Alpha***		
ILLIQ Groups	**Low RP**	**High RP**	**High RP - Low RP**	**Low RP**	**High RP**	**High RP - Low RP**
1 (Low)	1.01%	1.19%	0.18%	0.13%	0.04%	-0.09%
	(7.22)	*(8.94)*	*(1.71)*	*(2.53)*	*(0.73)*	*(-1.23)*
2	1.05%	1.32%	0.28%	0.10%	0.08%	-0.02%
	(5.56)	*(10.25)*	*(2.43)*	*(1.32)*	*(2.02)*	*(-0.18)*
3	0.97%	1.33%	0.36%	-0.04%	0.10%	0.14%
	(4.68)	*(11.18)*	*(2.59)*	*(-0.37)*	*(2.02)*	*(1.28)*
4 (High)	0.76%	1.23%	0.47%	-0.37%	0.18%	0.56%
	(4.01)	*(11.98)*	*(3.69)*	*(-3.6)*	*(3.13)*	*(5.25)*

Table 3.7: Regression Analysis

Time series average of firm-level Fama-MacBeth regression coefficients along with their t-statistics are reported for the period 1980-2013. *Beta* refers to sensitivity of a stock to market returns; *LN(Size)* refers to market capitalization of a stock; *BM* refers to ratio of book value to market value of a stock; *MOM* refers to previous 12-months returns; D_{RP} refers to residual price dummy which is equal to 1 for high residual price and 0 for low residual price; *IVOL* and *ISKEW* refers to idiosyncratic volatility and idiosyncratic skewness respectively; *IO* refers to percentage of institutional ownership; *ILLIQ* refers to Amihud's illiquidity measure.

		Limit to Arbitrage Variables			
	Baseline	IO	IVOL	ISKEW	ILLIQ
Intercept	0.1967	2.3150	2.9926	0.4215	0.5480
	(0.15)	*(1.48)*	*(2.52)*	*(0.32)*	*(0.39)*
Beta	-0.0261	-0.0551	0.0313	-0.0216	-0.0001
	(-0.22)	*(-0.51)*	*(0.28)*	*(-0.19)*	*(0.00)*
LN(Size)	0.0140	-0.1522	-0.0815	0.0058	-0.0001
	(0.24)	*(-2.08)*	*(-1.56)*	*(0.10)*	*(0.00)*
BM	0.0449	-0.1151	0.0223	0.0457	0.0025
	(0.59)	*(-1.09)*	*(0.31)*	*(0.60)*	*(0.03)*
MOM	0.0002	0.0013	-0.0001	0.0002	0.0006
	(0.19)	*(1.40)*	*(-0.08)*	*(0.19)*	*(0.62)*
D_{RP}	0.0584	0.1563	-0.0364	0.0511	0.0546
	(1.95)	*(4.42)*	*(-1.30)*	*(1.77)*	*(1.86)*
IO		0.0444			
		(8.27)			
(1 - IO) x D_{RP}		0.0042			
		(6.77)			
IVOL			-0.3096		
			(-5.14)		
IVOL x D_{RP}			0.0247		
			(2.87)		
ISKEW				-0.0033	
				(-2.65)	
ISKEW x D_{RP}				0.0003	
				(2.18)	
ILLIQ					-0.0260
					(-0.90)
ILLIQ x D_{RP}					0.0027
					(0.38)
Adj. R-Square	0.0425	0.0639	0.0510	0.0436	0.0462

Table 3.8: Sub-period Analysis and Price Cut-offs

Equal-weighted monthly portfolio returns along with their t-statistics are reported based on residual price (RP) for the sub-periods 1963-1987 and 1988-2013 in Panel A and Panel B respectively. Panel C reports the portfolio returns for the sample with price greater than $5 for the period 1963-2013. *1-F Alpha* refers to the intercept of portfolio returns on the excess market returns; *FF 3-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors; *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor. *High-Low* refers to return difference between highest and lowest price decile.

Panel A: 1963 - 1987

RP Groups	Raw Returns	1-F Alpha	FF 3-F Alpha	FFC 4-F Alpha
Low RP Decile	0.90%	-0.11%	-0.62%	-0.46%
	(3.42)	*(-0.64)*	*(-5.62)*	*(-4.13)*
High RP Decile	1.45%	0.59%	0.45%	0.23%
	(8.81)	*(7.05)*	*(7.36)*	*(3.99)*
High - Low	0.56%	0.70%	1.07%	0.69%
	(3.38)	*(4.6)*	*(7.65)*	*(5.04)*

Panel B: 1988 - 2013

RP Groups	Raw Returns	1-F Alpha	FF 3-F Alpha	FFC 4-F Alpha
Low RP Decile	0.76%	-0.57%	-0.71%	-0.09%
	(2.47)	*(-2.70)*	*(-4.06)*	*(-0.59)*
High RP Decile	1.23%	0.53%	0.42%	0.33%
	(10.65)	*(7.07)*	*(7.94)*	*(6.33)*
High - Low	0.47%	1.10%	1.13%	0.41%
	(1.95)	*(5.49)*	*(5.93)*	*(2.69)*

Panel C: Price > $5

RP Groups	Raw Returns	1-F Alpha	FF 3-F Alpha	FFC 4-F Alpha
Low RP Decile	0.94%	-0.15%	-0.41%	-0.10%
	(5.63)	*(-1.68)*	*(-6.58)*	*(-1.84)*
High RP Decile	1.30%	0.46%	0.38%	0.18%
	(12.19)	*(7.83)*	*(8.77)*	*(4.72)*
High - Low	0.36%	0.61%	0.79%	0.28%
	(3.45)	*(6.69)*	*(8.87)*	*(3.89)*

Table 3.9: Sentiment Analysis

Equal-weighted monthly portfolio returns along with their t-statistics are reported for low and high sentiment periods based on residual price (RP) for the period 1963-2013. *1-F Alpha* refers to the intercept of portfolio returns on the excess market returns; *FF 3-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors; *FFC 4-F Alpha* refers to the intercept of portfolio returns on the three Fama-French factors and Carhart's momentum factor. *High-Low* refers to return difference between highest and lowest price decile.

	Sentiment Periods	**Low RP Decile**	**High RP Decile**	**High - Low**
Raw Returns	**Low**	1.55%	1.30%	-0.26%
		(6.32)	*(8.84)*	*(-1.72)*
	High	0.31%	1.29%	0.98%
		(1.15)	*(7.13)*	*(5.65)*
1-F Alpha	**Low**	0.33%	0.41%	0.08%
		(2.47)	*(5.26)*	*(0.64)*
	High	-0.55%	0.55%	1.10%
		(-3.8)	*(5.32)*	*(7.09)*
FF 3-F Alpha	**Low**	-0.12%	0.23%	0.35%
		(-1.57)	*(3.85)*	*(3.14)*
	High	-0.68%	0.53%	1.21%
		(-6.15)	*(7.44)*	*(7.77)*
FFC 4-F Alpha	**Low**	0.08%	0.08%	0.00%
		(1.16)	*(1.47)*	*(-0.01)*
	High	-0.23%	0.28%	0.51%
		(-2.54)	*(4.45)*	*(4.24)*

Table 3.10: Stock Splits

Mean raw returns for stock splits along with their t-statistics are reported for December 1962 to December 2013. R_{1-12} , R_{13-24}, R_{25-36}, and R_{37-48} refer to buy-and-hold return from month 1 to month 12, month 13 to month 24, month 25 to month 36, and from month 37 to month 48 respectively from the month of stock split. Δ denotes differences in returns before and after the split. ΔR_{1-12} refers to difference between post-split R_{1-12} and pre-split R_{1-12}, ΔR_{13-24} refers to difference between post-split R_{13-24} and pre-split R_{13-24}, ΔR_{25-36} refers to difference between post-split R_{25-36} and pre-split R_{13-24}, ΔR_{37-48} refers to difference between post-split R_{37-48} and pre-split R_{13-24}. Number of stock splits used for analysis is 8,921.

	Pre-Split				Post-Split	
	R_{1-12}	R_{13-24}	R_{25-36}	R_{37-48}	R_{1-12}	R_{13-24}
Raw Returns	89.79%	45.01%	36.74%	28.90%	14.15%	13.41%
	-56.26	*-60.55*	*-22.04*	*-39.11*	*-24.7*	*-25.31*
Market-Adjusted Returns	71.77%	31.03%	23.59%	16.38%	3.15%	-0.29%
	-44.71	*-40.67*	*-14.06*	*-21.52*	*-5.25*	*(-0.51)*

	Post-Split minus Pre-Split Returns			
	ΔR_{1-12}	ΔR_{13-24}	ΔR_{25-36}	ΔR_{37-48}
Raw Returns	-75.64%	-31.60%	-23.33%	-15.49%
	(-44.60)	*(-34.61)*	*(-13.33)*	*(-17.03)*
Market-Adjusted Returns	-68.62%	-31.32%	-23.88%	-16.67%
	(-40.05)	*(-33.01)*	*(-13.49)*	*(-17.60)*